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Research Article

A general model of watershed extraction and representation using globally optimal flow paths and up-slope contributing areas

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Abstract. Many modern hydrological models require data inputs provided by automated digital terrain analysis functions incorporated into GIS. These inputs include fields representing surface flow directions, up-slope contributing areas, and sub-catchment partitions. Existing raster-based terrain analysis tools, including both those in off-the-shelf GIS packages and those in the recent literature, were designed to work with digital elevation data in mountainous topography. For highly variable topography, which may include large flood plains, lakes, wetlands, and other relatively flat areas, existing tools cannot accommodate the variable signal-to-noise in the source elevation data without significant human intervention to handle special cases. A general model for calculating flow directions, up-slope contributing areas, and sub-catchment partitions that automatically adapts to the variable information content of grid-based elevation data sets is presented here. The model uses a combination of breadth-first search and global optimization to extract the maximum amount of signal from any location within the data. The model is demonstrated to work well in handling topography dominated by large flood plains, lakes and other flat areas without the need for a large number of empirical rules. An important contribution of the approach is the handling of explicit hydrologic features, which makes the spatial representation closely related to hydrological processes. The results have important implications for developing hydrological models that are tractable in large, heterogeneous watersheds using moderate resolution data.

1. Introduction

Many distributed-components hydrological models rely heavily on GIS techniques to provide them with co-varying fields of topographic flow paths, soil hydraulic properties, and vegetation. In moderate-to-steep topography, up-slope contributing areas, surface flow directions and catchment boundaries are needed in rainfall-runoff modelling, non-point source pollution modelling, and in distributed models of forest ecosystems. With the widespread availability of grid-based digital elevation models (DEMs) their use has become ubiquitous and GIS algorithms designed to extract hydrological properties from them almost routine. However, even the most recent research algorithms for up-slope area and flow path representation

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are limited to working in relatively small, steep catchments on clean DEMs. Although there have been methods to handle DEM noise, e.g. pits and dams, there is as yet no general method for handling all hydrologically significant features of large watersheds, such as wide flood plains, lakes, reservoirs, wetlands, and upland flat areas. The existing body of work on this subject suggests that these features require specific, over-parameterized models for their handling, often at the expense of diminishing the information content of the DEM (Tarboton 1997, Mackay and Band 1998). We argue that such feature specific rules hinder the development of generic, robust tools for watershed characterization. The need for a large number of parameters makes the existing tools prohibitive for modelling large watersheds at moderate resolutions. An alternative approach to terrain analysis is presented here in which global search techniques and optimization reduce the need for an excessive number of feature specific parameters.

This work is motivated by a need for improved integration of GIS and distributed hydrological modelling. Developments in GIS have lead to more efficient implementation and application of lumped and distributed simulation models. Numerous comprehensive reviews (Moore *et al.* 1993, Wilson 1996, Moore 1996, Paniconi *et al.* 1999) describe how GIS addresses issues of data quality, data model—numerical model integration, parameter aggregation, and hydrologic system representation. Our work focuses primarily on this latter issue of representation. By representation we are in part referring to the common framework within which data are collected and organized, simulation models are designed, and model results are presented. Numerous such frameworks exist. Grid-based, contour-based, TIN (triangulated irregular network)—based, and purely lumped models, are example frameworks within which simulation model inputs are derived. Examples of grid-based models integrated within either commercial or custom GIS are DHSVM (Wigmosta *et al.* 1994), RHESSys (Band *et al.* 1993) or other models that use TOPMODEL (Beven and Kirkby 1979), SWAT (Arnold *et al.* 1993), and Vieux *et al.* (1996). In the case of models like RHESSys and SWAT the grid-based data inputs are further organized into hydrologically significant features, or functional units for input to the simulations. Functional units are another part of representation that gets at the underlying conceptual representation of hydrological systems. Sub-catchments and hydrologic response units are the most common types of functional units that have been extracted from DEMs and represented within GIS.

Hydrologic representation based on only catchments and hydrologic units does not adapt easily to general watershed representation in which water bodies and wide flood plains may have to be represented. By forcing the restricted representation on these areas unrealistic models may result. For example, water bodies are often represented as wide streams during watershed extraction; they are in turn simulated as wide streams in hydrologic models. Mackay and Band (1998) suggest that this is increasingly a common problem now that hydrologic models are applied outside of small, mountainous watersheds. Lakes are common features in the glaciated watersheds of the Upper Midwest of the United States and other areas around the Great Lakes. Reservoirs are important features in large watersheds in mountainous areas, and so they have to be represented as we scale up hydrologic modelling to a regional extent. If GIS are to support a wide variety of hydrologic modelling then it is increasingly important that automated watershed representation be adaptable to a wide range of feature types.

2. Prior results

This paper addresses grid-based DEMs, which are widely available and used in a variety of applications including flow path algorithms that support hydrological modelling. The first of these flow path algorithms were the steepest descent, or D8, algorithms of O'Callaghan and Mark(1984) and Marks *et al.* (1984). D8 has been widely used to partition watersheds into sub-catchment areas (Band 1986a, Jenson and Domingue 1988, Tarboton *et al.* 1991), as well as calculating up-slope contributing area (Morris and Heerdegen 1988, Jenson and Domigue 1988, Band 1989, Ehlschlaeger 1989, Lammers and Band 1990, Martz and Garbrecht 1992, Moore 1992, Garbrecht and Martz 1997, Mackay and Band 1998, Wilson and Gallant 1998). Fractional, or F8, flow algorithms partition flow from a cell to all of its eight neighbors by weighting flow according to relative slope (Freeman 1991, Quinn *et al.* 1991). Uncertainty associated with F8 weighting schemes prompted development of a flow-tube analogy in which flow across a planar surface is resolved for each cell using both aspect and gradient of the plane (Lea 1992, Costa-Cabral and Burges 1994, Tarboton 1997).

Regardless of how flow is routed all cell-based algorithms attempt to find surface flow directions and up-slope areas either during an ascent from concave points on the DEM or descent from convex points on the DEM. The information gathered by these algorithms is affected by error in the DEM, such as pits or dams. Pits and dams occur as a result of insufficient or missing data during DEM production. In small, steep watersheds, pits and dams are usually negligible due to the high local topographic relief. However, in flatter areas of larger watersheds or in lake-dominated areas, pit depths and dam heights often exceed local true elevation differences. Figure 1 shows the different effects of DEM errors in steep and flat areas, respectively, and figure 2 shows how these errors propagate to flow path searching algorithms. The sensitivity of these algorithms to DEM noise results in a number of pathological drainage conditions, including gaps (Chorowicz *et al.* 1992, Costas-Cabral and Burges 1994) and loops (Band 1989, Smith *et al.* 1990).

A number of simple rules have been devised to overcome gaps and loops, including pit filling (Marks *et al.* 1984, Band 1986a, Jenson and Domingue 1988, Martz and Garbrecht 1992), dam breaching (Garbrecht and Martz 1996), and slope tolerances (Band 1989). During pit filling a surface is formed by filling a pit to some new pour height. This produces a surface through which flow paths can be inferred from the surrounding topography (Martz and Garbrecht 1997). Slope tolerances permit flow connections as long as the slope gradient of a cell is below some threshold value. They also allow for catchment area spillage over shallow divides and into adjacent catchments, and so such simple rules should be used with caution.

Bennett and Armstrong (1996) used a bit-mapped classification scheme to place each DEM cell into one of six categories based on the topographic form of its local and extended neighbourhoods. Cells with similar topographic form were aggregated into networks that represented stream channels and basin divides. A similar image processing approach was first demonstrated by Toriwaki and Fukumura (1978) and later extended by Band (1986b) for hydrological applications. Bennett and Armstrong (1996) further extended this image processing in that the stream and divide networks are extracted from the DEM and stored in vector-based data structures. To remove erroneous pits in flat areas, a 'best first' (maximum descent/minimum ascent) method is used to find down-slope streams. However, human intervention is needed to define an application specific threshold and to decide whether to make the connection or not.

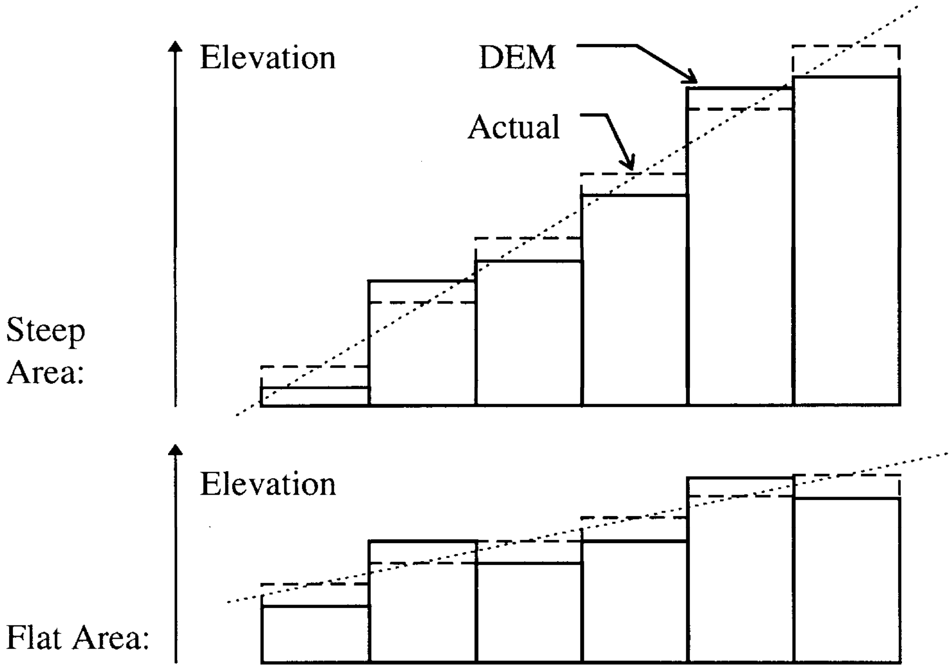

Figure 1. Contrasting signal-to-noise ratios in steep and flat areas of a DEM. The magnitude of errors are identical for the two areas, but dams and pits are formed in flat areas.

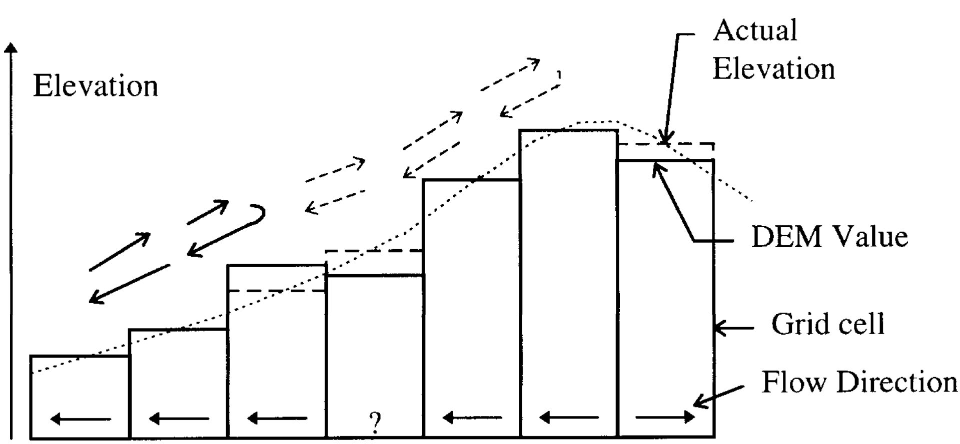

Figure 2. Effects of errors in a DEM on the calculation of flow directions and up-slope areas.

Mackay and Band (1998) introduced the concept of *a priori* identification of lakes and other flat features on the DEM, which improved the overall catchment area and flow path calculations, and guided the selection of appropriate rules for handling these hydrologically significant features. Their approach allows for selective positioning of different rules and tolerances within different areas of the DEM, which essentially maximizes the gain of information from the data. Liang and Mackay (1997) refined this approach by introducing a rule-based heuristic that minimizes the loss of DEM information content that typically occurs with the introduction of additional rules that require human interaction. Here we generalize and extend these results in order to develop a general tool for acquiring topographically-based hydrologic information from a wide range of watershed areas and landscape types.

3. Methods

3.1. *Breadth-first versus depth-first search*

Following Marks *et al.* (1984) up-slope contributing areas are identified by some form of recursive upward climb from a specified outlet cell. From a starting cell an up-slope cell is found and the algorithms proceed by moving to the up-slope cell and continuing the search until a divide is encountered. A depth-first search strategy is usually used by these algorithms. A depth-first search path is first identified completely to its source at a divide before any other paths are followed. Areas are accumulated on the recursive unwinding. While this is a simple and efficient way to accumulate contributing areas, it gives correct up-slope contributing areas only if the underlying flow path is identified correctly early in the search. However, it is not at all effective in searching for flow paths in areas of low to moderate local relief. Unlike steep areas on a DEM flow direction information in more moderate areas is usually either disrupted by noise or undefined (*i.e.*, perfectly flat), and so prior to accumulating the up-slope areas the flow paths must be approximated.

An alternative to the depth-first search algorithm is breadth-first search. Figure 3 shows the search sequence of depth-first and breadth-first search algorithms operating in a two-dimensional grid-based search space. Depth-first search exhausts one path before going to the next, while breadth-first search visits all immediate neighbors of one node before proceeding to the next node. In effect, the breadth-first search has an advancing front line consisting of nodes held either in a queue or a stack. Initially, the front line only includes the starting nodes. After the nodes in the front line are all visited, any of their respective unvisited immediate up-slope neighbors are added to the front line and old nodes in the front line are deleted. The front line continues to expand until all nodes have been visited.

Although depth-first and breadth-first algorithms both visit one node at a time they differ in their search bias. Depth-first search follows a path based on the first node encountered in the immediate neighbourhood. Since the decision to advance is based solely on a single cell-to-cell connection the depth-first approach is sensitive to DEM noise. However, the search pattern of breadth-first search can be viewed as giving all nodes in the neighbourhood equal status as members of the advancing front line. The size of the queue representing the front line grows and shrinks according to the distance outward the algorithm must search in order to find a reasonable flow path. The result of this adaptive neighborhood search is that the flow paths are not sensitive to noise as long as there is topographic information somewhere within the front line.

Although the search strategies differ they should produce identical flow directions and up-slope contributing areas in areas of high signal-to-noise, such as steep areas on DEMs. In flat areas the two algorithms may result in dramatically different flow paths. Flat areas are defined as those areas on a DEM where noise disrupts some or all the relative elevations of neighbouring cells. Three distinct categories of flat areas are identified for the purpose of our analysis. First, as a result of DEM scale, data truncation and noise, flat areas in DEMs can be perfectly flat, i.e. all the cells in the flat area are at the same elevation. In this case, flow directions are undefined. Second, small relative elevations of neighboring cells may be overwhelmed by DEM

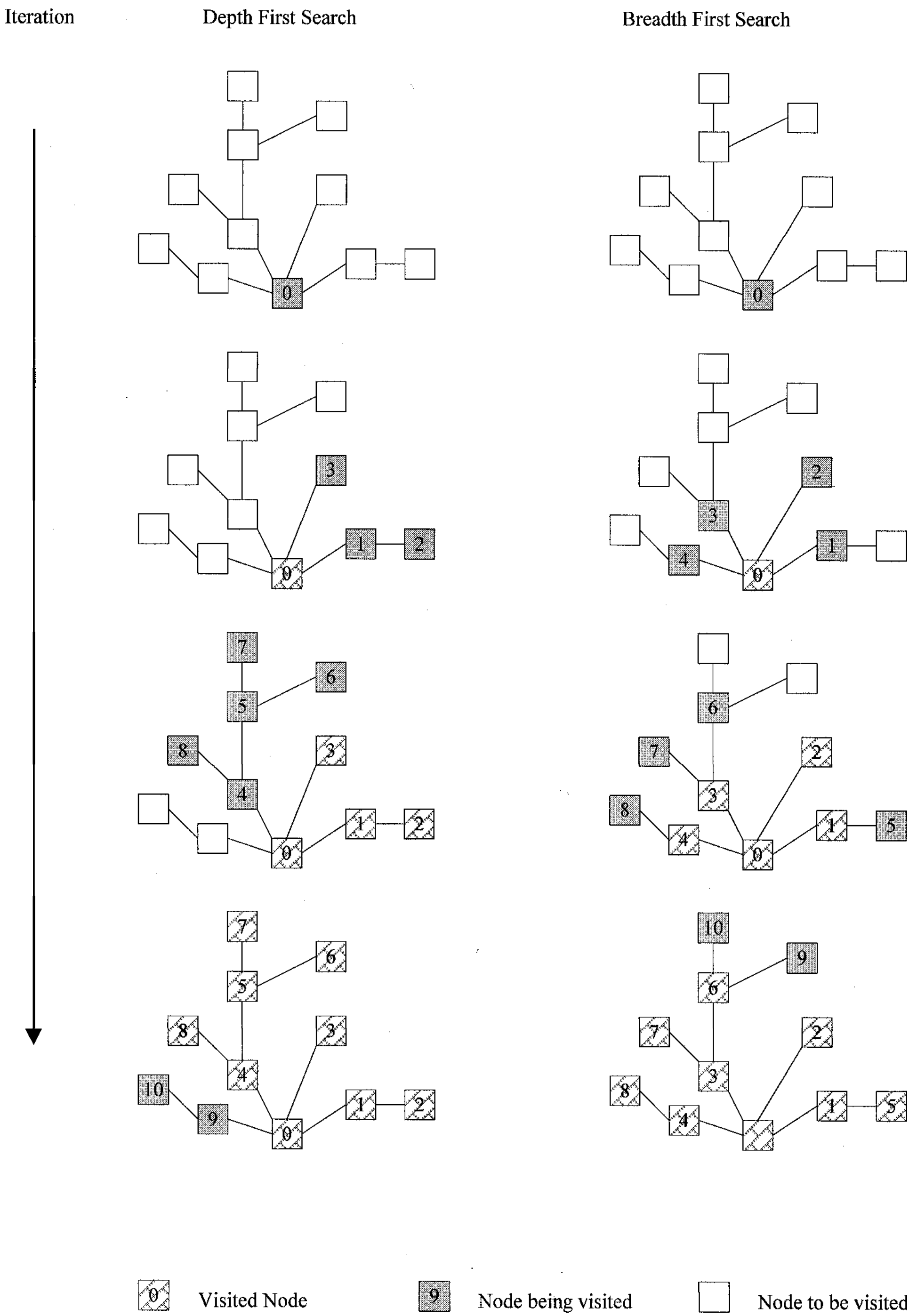

Figure 3. Progression through time of depth-first search and breadth-first search algorithms. Each square represents a node in the search tree and a cell on a grid-based DEM. Line segments represent connections between cells. The numbers in each cell represent the order in which the cells are encountered in the search. Depth-first search tends to sweep across the search space, while breadth-first expands outward from a starting location.

noise. In this case, the flow directions are meaningless and are also considered undefined. In both of the above two cases, artificial flow paths within flat areas have to be created according the elevation information of the surrounding cells for three reasons: First, in order to conform to reality as close as possible; second, in order to preserve continuity of flow paths for use in hydrological models; and last and most important, flat areas occur most often within valley bottoms, and so up-slope areas would not be fully accumulated for large watersheds if flat areas were not fully marked. We observe that many noisy areas on a DEM occur in the hydrologically most active areas, such as in flood plains and riparian areas. As such, it is important that flow paths through these areas be closed using the maximum amount of topographic information possible. Figure 4 shows the different flow paths produced by the two search algorithms on a small piece of a flat DEM. Since the cells on a DEM are connected to one another directly or indirectly, the depth first search algorithm tends to traverse all the cells in no more than a couple of entangled paths, resulting in unrealistic flow paths. The up-slope area image accumulated with this kind of flow path will show the flat areas as unrealistically wide streams where neighboring cells inside often have opposing flow directions. Since the breadth first search algorithm depends less upon making a decision with little or no information it is not expected to produce the wide streams.

The third category of flat objects, which typically accounts for most of the flat areas on DEMs, has low signal-to-noise with a number of cells having erroneous relative elevations, but a topographic signal exists within a larger neighbourhood. Depth-first search often fails to find this regional topographic signal because it cannot see more than one point-to-point connection at a time. When it changes flow direction of a potential 'noisy' cell according to this single connection more error may be introduced. However, the advancing front line of the breadth-first search is more tolerant of a potentially noisy cell, and so it preserves more of the original information in the DEM. The algorithm is as follows:

```
For each cell i on the front line {
        For each neighbour j of i {
                If (gradient(j)< flat_threshold) {
                        If (j flows to a cell in the front line) {
                                Do nothing;
                        }
                        Else {
                                Force j to flow to i;
                        }
                }
        }
}
```

The breadth-first algorithm can leave a noisy cell's flow direction unchanged as long as it flows to one of the cells on the front line. Thus, only noisy cells that do not flow to the front line are considered true noise and are forced to flow to the front line. Since fewer cells are changed based on the information content of a single pair of cells, the resulting flow paths are more representative of the information content of the DEM.

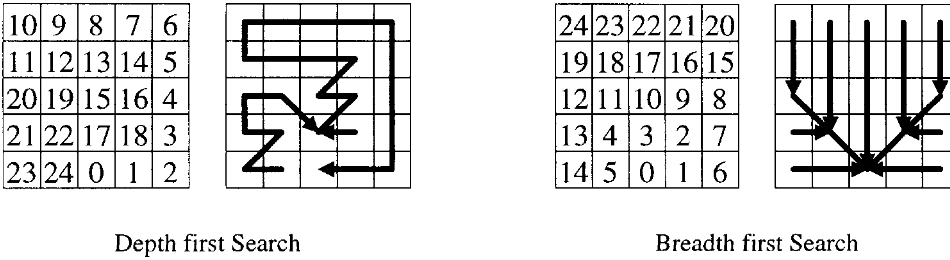

Figure 4. Behaviour of depth-first search and breadth-first search on a small flat DEM. Each small square represents a DEM cell. The numbers in the cells indicate the searching sequence, and the line segments with arrow heads indicate the resulting flow directions. Depth-first search forms long, twisted paths because cell flow directions are modified without considering the flow directions of surrounding cells. Breadth-first promotes the formation of parallel flow lines because it forms preferential flow towards the starting location.

3.2. *Globally optimal feature handling*

Mackay and Band (1998) represent a watershed as a cascading sequence of objects, which may be single grid cells or clumps of cells representing hydrologically distinct features. Each watershed object has methods for incorporating it into a topologically connected set of flow paths. Different object methods tune the extraction of information from the DEM. An optimization algorithm developed by Liang and Mackay (1997) performs this tuning without human intervention, but fails in flat valley bottom areas and where objects straddle divides. The breadth-first search algorithm described in the previous section overcomes the first problem. The second problem is that objects that straddle divides must be segmented into two or more different subcatchments. A solution to this is presented in this section.

As with previous algorithms (Marks *et al.* 1984, Band 1986, 1989, Mackay and Band 1998), a slope threshold differentiates between noisy cells and clean cells for each flat area. If a cell has a slope gradient that is below some threshold, it is considered a noise cell and its flow direction may be modified to ensure a connected set of flow paths. If the slope threshold is at or above the threshold, then the cell's drainage direction is defined as the direction of steepest descent, in the case of D8 flow paths, or in multiple directions with flow fractionated by relative slope, in the case of F8 flow paths. In steep areas and in perfectly flat areas, the slope threshold is normally set to zero. In other flat areas, an optimal slope threshold must lie somewhere between zero and the maximum gradient of the area. If the threshold is set to a value below the optimum value, then the resulting flow paths may be disconnected. However, if the threshold is set too high, then more cells than necessary will be considered noisy and the drainage path will become over-connected, resulting in wide streams. We define the optimal threshold to be the lowest slope threshold that allows for contiguous marking of the flat object. For all flat areas that are not water bodies we use an optimal slope threshold. We recognize that more sophisticated methods could be developed to handle flat areas, but it is our goal to have a general, adaptable approach rather than one based on handling special cases.

In order to quickly find the optimal threshold for each flat object, we use a binary search method. For each flat object we define (1) a pass threshold, T_p, and (2) a fail threshold, T_f. The pass threshold is initially high enough to modify the flow direction of a given cell, while the fail threshold is low enough that the cell flow

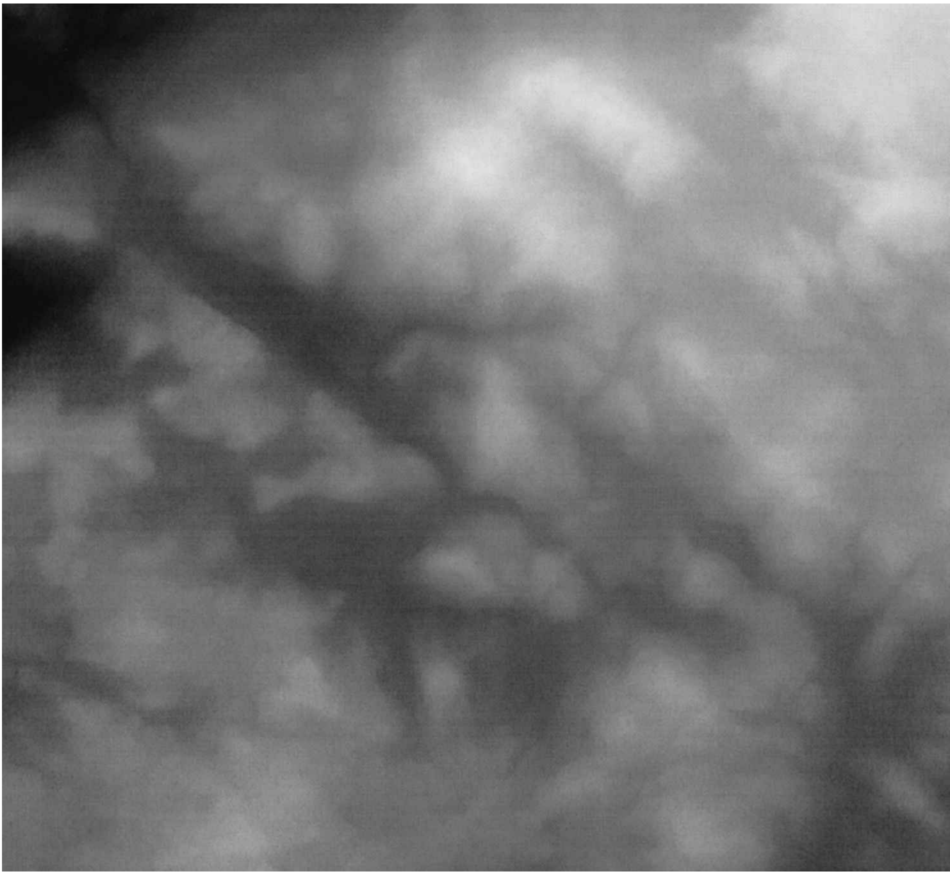

Figure 5. DEM for the Turkey Lakes Watershed, in central Ontario.

direction must be defined using one of D8 or F8 flow. Initially, the fail threshold is set to zero and the pass threshold is set to a predefined high value, such as the highest gradient in the area. A precision parameter, P, allows the optimization algorithm to halt when the difference between the pass and fail thresholds is small enough to be considered negligible. Each cell's gradient is compared against these thresholds. The gradient values are calculated as

$$Grad(i,j) = \frac{\sqrt{((I(i+1,j) - I(i-1,j))^2 + (I(i,j+1) - I(i,j-1))^2}}{2N} \quad (1)$$

where $Grad(i,j)$ and $I(i,j)$ are the gradient and elevation values at row i and column j of the DEM, respectively, and N is the DEM cell size in the same unit as the elevation values. We normally set the precision to be the smallest gradient obtainable along a cardinal direction. For a DEM with one metre vertical resolution, this gives $P = 1/(2N)$.

The pass threshold T_p is used to mark flow paths inside a flat object. If the resulting flow paths allow all cells inside the flat object to be reached, then the difference between T_p and T_f is checked. If the difference is less than P, then T_p is the optimal threshold. Otherwise, the pass threshold may be too high, in which case it is adjusted to the half point between the pass and fail thresholds. If T_p does not allow for marking all cells inside the flat object then it is considered too low, at which point its value is increased by 2 ($T_p - T_f$) and the fail threshold is changed to the previous pass threshold. The above process is repeated until the optimal threshold is found. The following is the pseudo-code of the binary search for an optimal threshold of an object:

```
P = 1/(2N);
Tp = 0.05;
Tf = 0;
while(Tp - Tf > P)
{
        Use breadth-first search to mark the object with Tp;
        If(object all marked)
        {
                Tp = (Tp + Tf)/2;
        }
        else
        {
                tmp = Tf;
                Tf = Tp;
                Tp + = 2(Tp - tmp);
        }
}
```

With the above algorithm a single object's optimal threshold can be determined, but since we do not know the outlets for an object in advance, it would not be reasonable to isolate each object and optimize its threshold independently of the other objects. However, we can try to mark the whole DEM and then adjust the thresholds for all objects using the above algorithm. We then iterate until all the objects have optimal thresholds. The following is the pseudo-code of this global optimizing algorithm:

```
bool bAllOptimal = false;
while(!bAllOptimal)
{
        Mark the whole DEM, each object with its individual thresholds;
        bAllOptimal = true;
        For each flat object Oi,
        {
                If (Tp of Oi is not optimal)
                {
                        Adjust Tp and Tf of Oi;
                        bAllOptimal = false;
                }
        }
}
```

Watershed marking begins along the edge of the DEM. All DEM edge cells are considered possible outlets and are sorted according to their elevations, following an approach first presented by Ehlschlaeger (1989). Flow paths are searched from all of the outlets starting from the lowest unmarked edge cell. Thus, objects are marked from all possible directions, which allows for their partitioning into multiple catchments when they straddle divides.

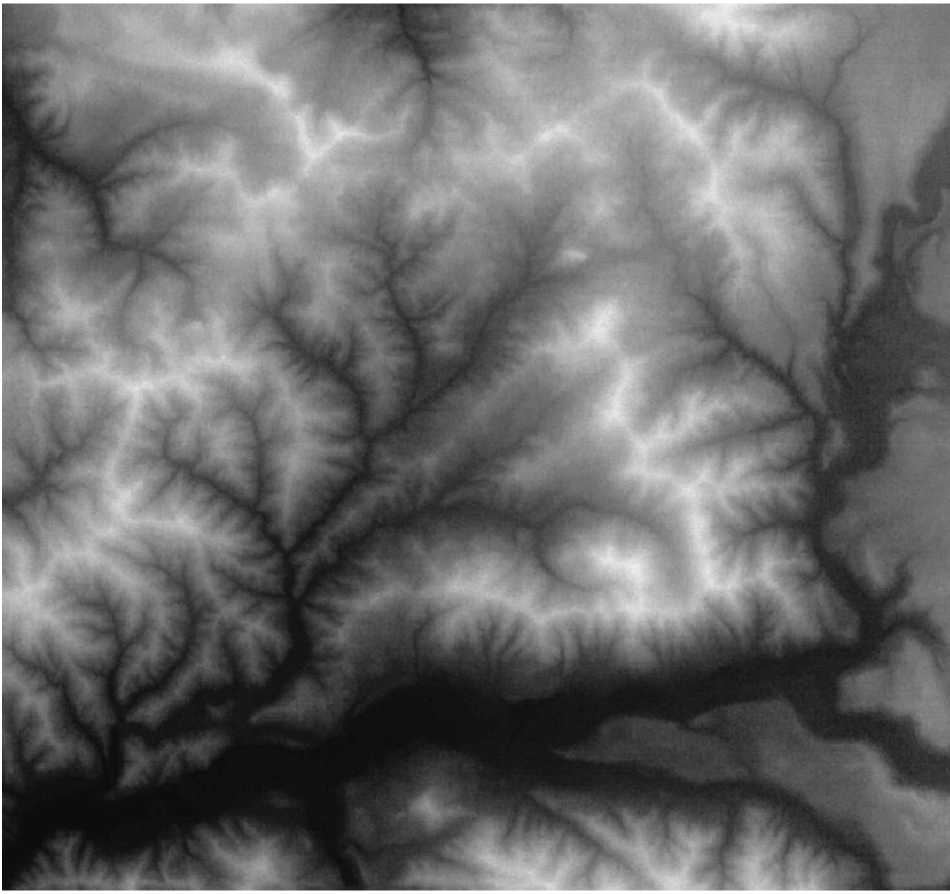

Figure 6. DEM for the H. J. Andrews watershed, which is located in the Cascades of central Oregon.

The above global optimization algorithm may produce excessively high slope thresholds for some objects that straddle divides. A divide straddling object must be marked simultaneously from all directions to be optimally marked. However, it may in fact be reached at different iterations from different directions if there are different numbers of flat objects in series within each respective catchment. Objects are optimized in the order in which they are found during an uphill climb. The divide straddling object will always be the last object found during a climb, and it will be reached first from the direction that has the fewest objects in series. It may then be optimized from the perspective of one valley outlet while the marking processes from the other valley outlets are optimizing objects downstream. By the time the divide straddling object is reached from a second path, its threshold may already have been erroneously optimized. To solve this problem a second pass is made of all objects. In this pass each object's threshold is verified from all possible outlets. If the fail threshold succeeds in marking the whole object, then this object may not have been optimally marked and its optimization is repeated while holding all other objects' thresholds unchanged. The second pass over the objects is relatively quick since it can use the knowledge of flow paths gained in the first pass.

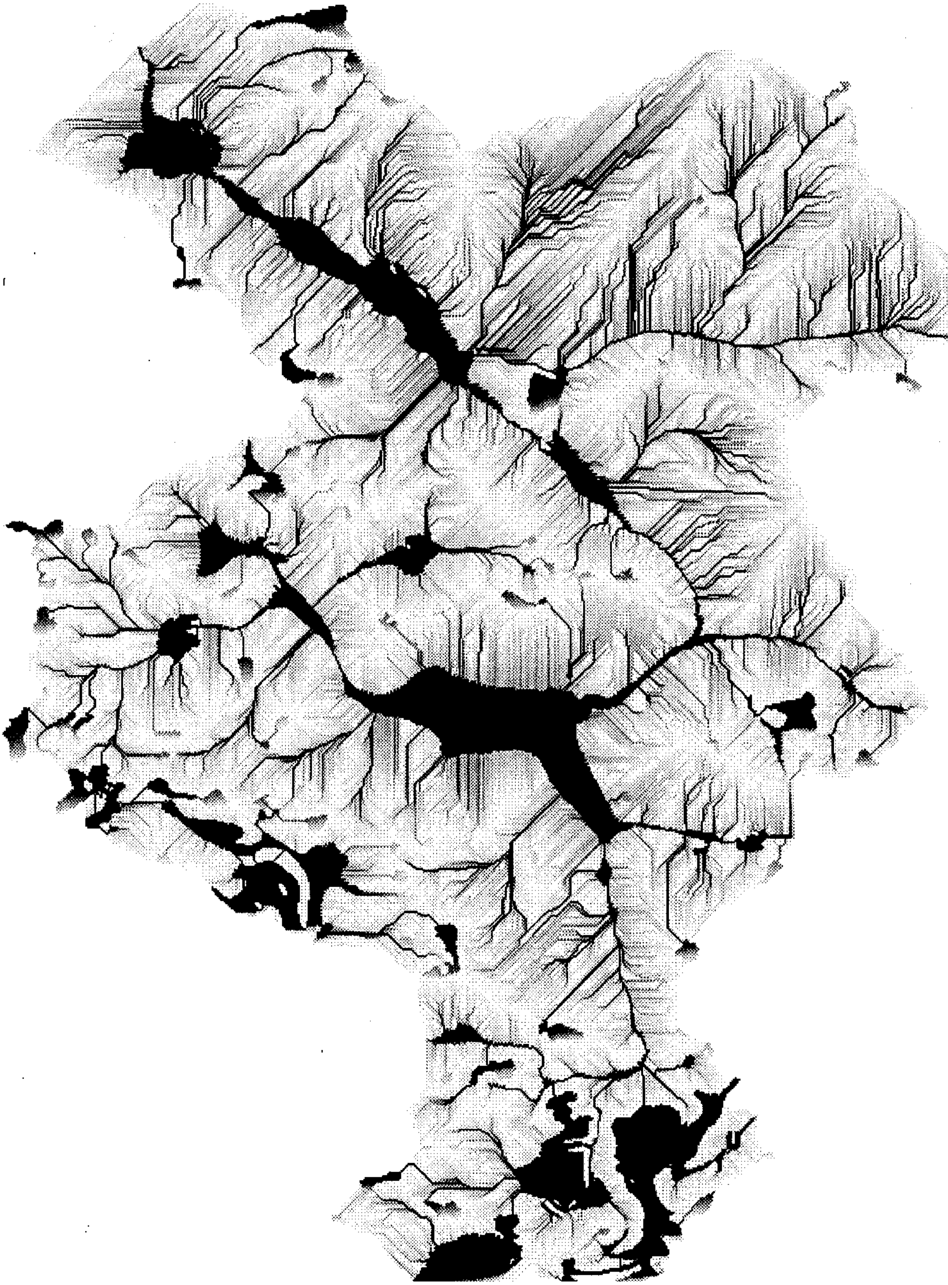

Figure 7. The Up-slope area image of Ontario site produced using (*a*) depth-first search without feature optimization, (*b*) depth-first search with feature optimization, and (*c*) using breadth-first search with global feature optimization.

Water bodies, such as lakes and wetlands, are extracted using boundary marking (Mackay and Band 1998) rather than optimization. The boundary of a water body is marked as an absorbing boundary for all flow it receives. The area draining into the absorbing boundary is propagated to the outlet cell of the water body.

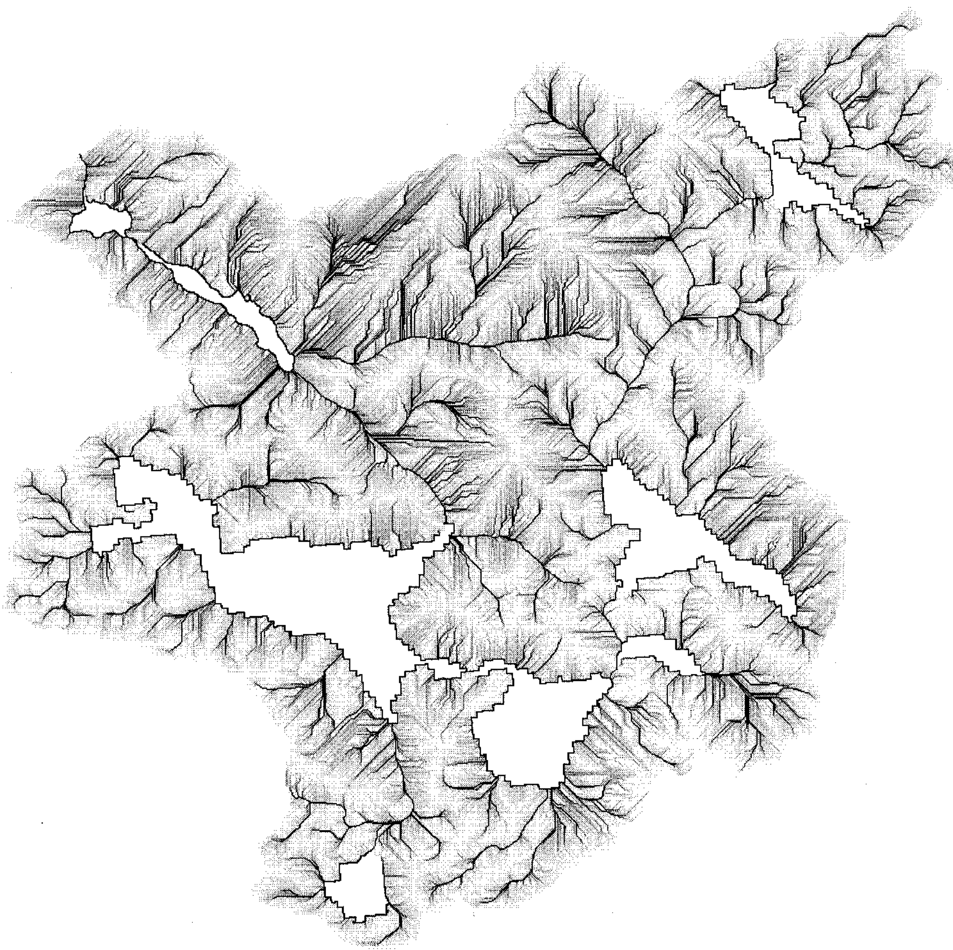

Figure 7(*b*).

When up-slope areas are later used to define a stream network and associated sub-watersheds, a topological connection is made between the outlet stream link and all incoming stream links to the water body. Topological connections are also made from surrounding subcatchment areas to the water body. This enables us to explicitly route water into water bodies, and then move water to the outlet using any amount of hydrologic sophistication as deemed necessary by specific applications. This feature-based approach provides for a more flexible representation of the watershed since it does not explicitly define how water moves through the water body, but it retains the water body as a topologically connected component. It has been used to clearly separate terrestrial and aquatic components of glaciated watersheds for hydrologic modelling (Band *et al.* 1996) and watershed representation (Robinson and Mackay 1996).

4. Results

We tested our model of topographic characterization with two DEMs of contrasting topographic character. One data set is from a lake-dominated topography

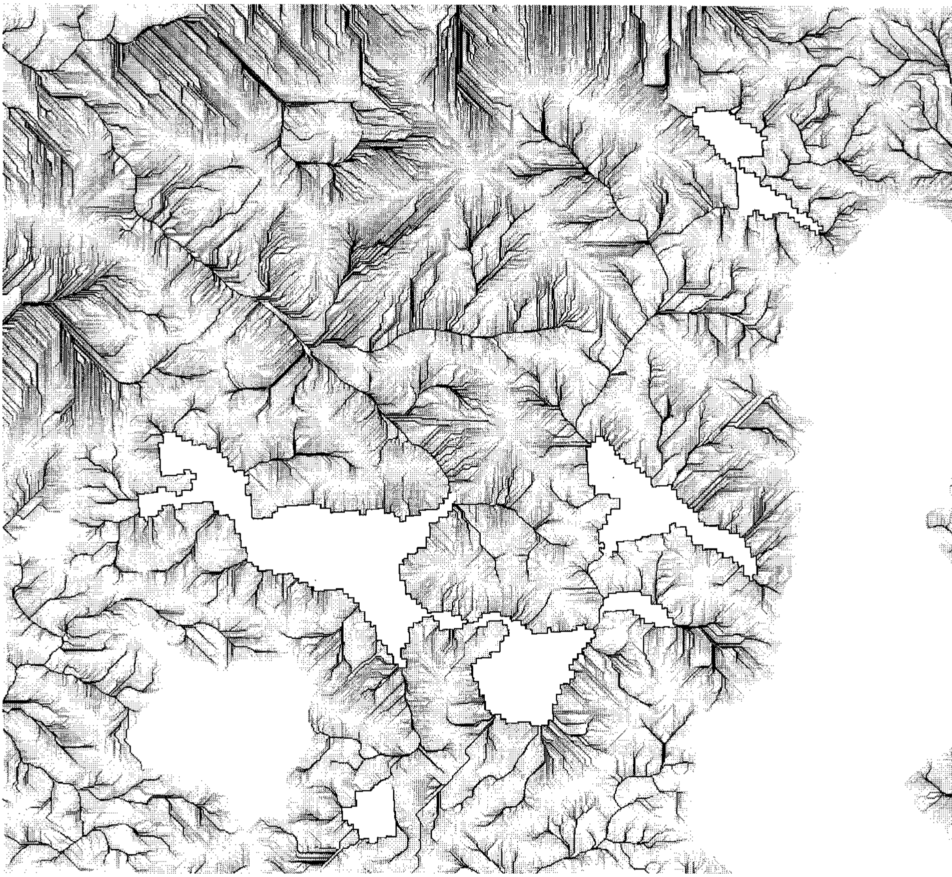

Figure 7(c).

in the Algoma Highlands of central Ontario, Canada. The area has approximately 350 meters of relief, which is exceptional for Great Lakes area watersheds (Jeffries *et al.* 1988). Otherwise, it is characteristic of the glaciated upland areas around the Great Lakes, with a predominance of nested lakes, wetlands, and other flat areas. The DEM (figure 5) for this area was derived from a contour map using TOPOG (CSIRO 1992), which uses a thin plate spline interpolation algorithm (Hutchinson 1989). The second data set is of a 1000 km^2 area within the Cascade Range in Oregon, which has over a 1000 m of relief as well as large valley bottoms and reservoirs. The data is a mosaic of USGS level 2, 7.5 minute quad DEMs (figure 6).

To test the new algorithms we used three different approaches:

1. depth-first search with no global optimization (DF) (Band, 1989);
2. depth-first with global optimization (DFG) (Liang and Mackay, 1997); and
3. breadth-first with global optimization (BFG).

The results for the Ontario and Oregon sites are shown, respectively, in figures 7 and 8. Figure 7(a) shows the results for the Ontario DEM generated with the DF approach. In this image, entangling flow paths in the flat areas form wide streams, which is a characteristic result of depth-first search. In addition, only part of the watershed is marked. Although raising the slope threshold will increase the size of

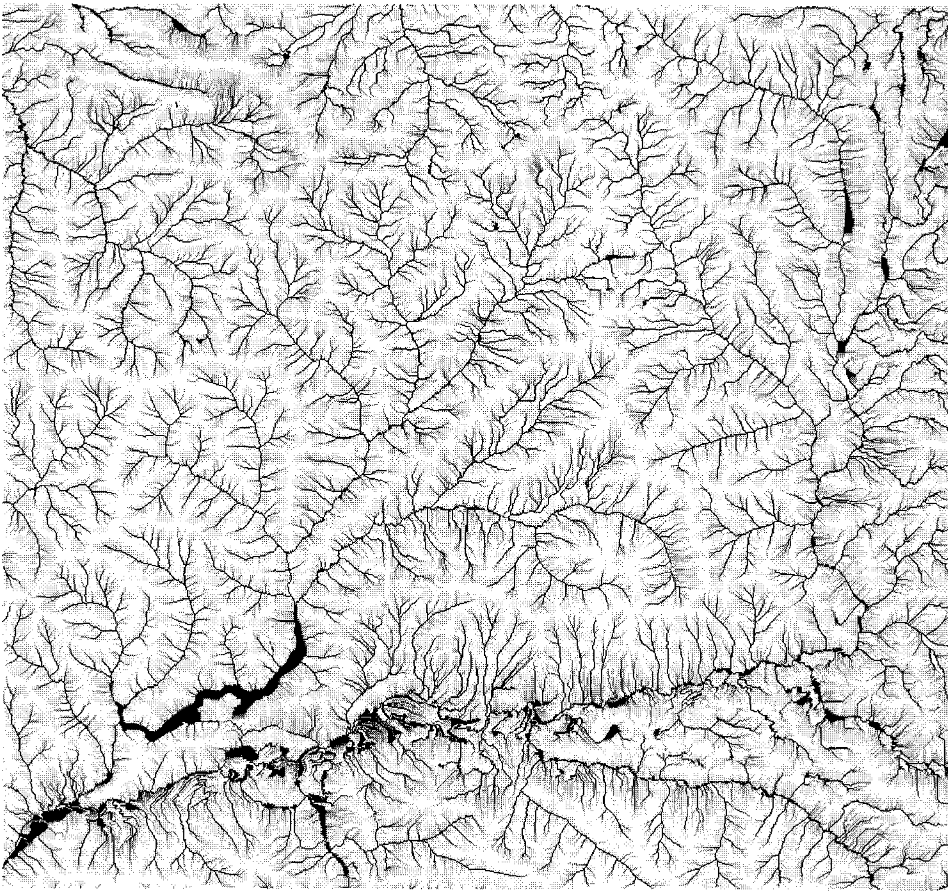

Figure 8. The up-slope area image of Oregon site produced using (*a*) depth-first search, and (*b*) breadth-first search.

the marked region, it will also produce a larger number of wide streams. Figure 7(*b*) was generated using DFG. By isolating flat areas and optimizing each non-lake flat object's flow path an improved watershed representation results. The watershed is completely marked and flow pathways are clean with no erroneous wide streams. It should be noted that the DFG algorithm did not work well for all flat areas. We had to change the classification of the two non-lake flat objects near the outlet of the watershed to lake in order to avoid this problem. This result is due to the fact that the optimization criteria was designed to eliminate wide streams, which in some areas may be inconsistent with the requirements of the depth-first search algorithm to fully mark a flat area. Figure 7(*c*) was generated using BFG. With no modification to any object type, the breadth-first search climbs through the non-lake flat areas without forming entangled flow paths. One may note that some flow paths on the right edge of the main watershed extend over the divide. This is due to the quality of the DEM, which is derived from a watershed map in which areas outside of the main watershed were not as carefully mapped as areas within the watershed. As a result, the up-slope area image contains large holes. This prevents some flat areas

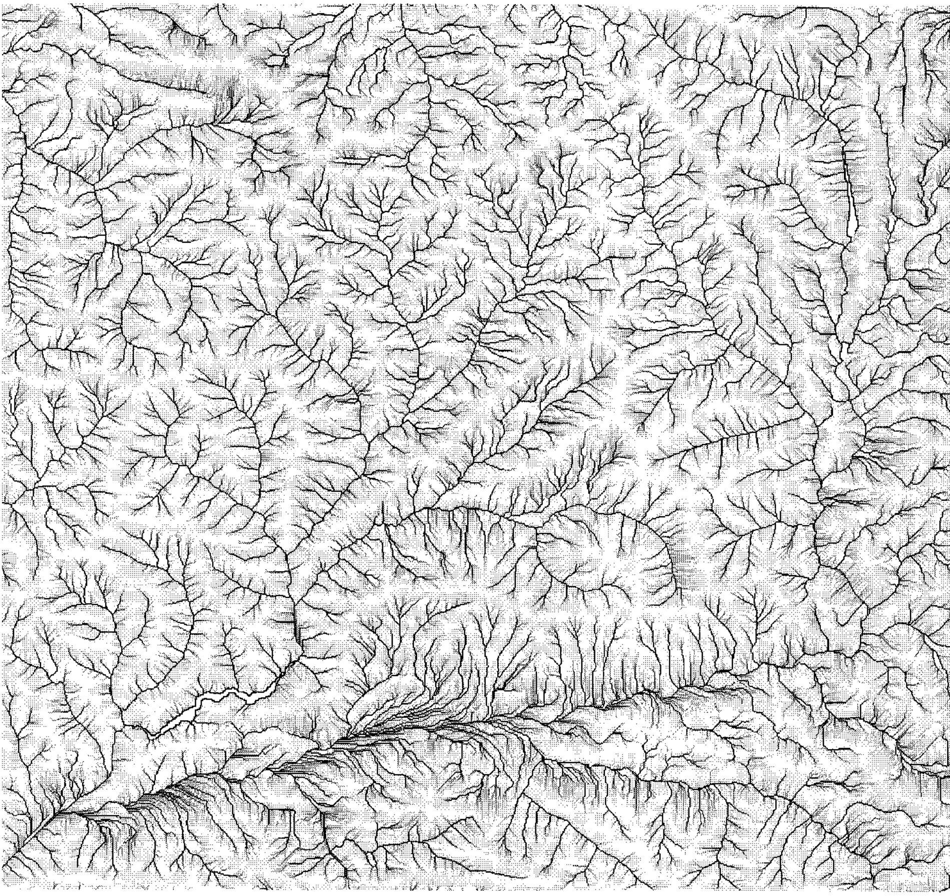

Figure 8(*b*).

that straddle watershed ridges from being searched from all outlets, and so their slope thresholds are not fully optimized.

Figure 8 shows the results for the Oregon site. Figure 8(*a*) was generated using the DF algorithms. Again the depth-first search forms entangled flow paths in all flat areas, and most notably in the valley bottom along the south edge of the DEM. No DFG is shown here, as it did not differ from DF and the valley bottoms were already marked using a slope threshold of zero. Figure 8(*b*) was generated using BFG. No global optimization was required for this data set as there were no significant non-lake flat objects required. In steep areas the results bear minimal difference to the DF approach, but in flat areas the erroneous wide streams are eliminated. In the flattest areas the BFG does tend to produce near-parallel flow lines, which is to be expected. In general, convergent flow lines are curvilinear and bend towards the regional flow direction. These results can be explained by examining the shape of the advancing front line as the breadth-first search algorithm moves through the data. Figure 9 shows snapshots of the front line in the form of a greyscale image. Lighter areas in the image correspond to earlier stages in the search, while darker parts of the image correspond to later stages of search. Also shown on this figure are the positions of the front line at every 12th interval; they may be thought of as contours formed around pour points. Concentric search areas are formed around water bodies, which means that whole water body objects are treated as single pour points in the topography. The curvilinear flow in the large valleys can be explained by the shape of these contours, which tend to be semi-circular with their centroids positioned downstream of the contour.

Once up-slope areas and flow paths are known a number of hydrologically relevant data sets can be produced efficiently. Figure 10 shows the F8 (Freeman 1991, Quinn *et al.* 1991) flow paths for two selected watershed areas. F8 flow is more representative of flow in convergent topography. It is commonly used in topography-based hydrologic indices used in models based on TOPMODEL (Beven and Kirkby 1979). Figure 11 shows the same watershed areas partitioned into sub-catchment areas, which are used to construct databases for hydrological modelling (Band 1989, Lammers and Band 1990). These data products are primary inputs to many hydrologic models, including RHESSys (Band *et al.* 1993) and SWAT (Arnold *et al.* 1993).

5. Discussion

This paper has addressed some shortcomings of existing grid-based watershed extraction and representation algorithms for low relief areas by using a combinations of object-based rule optimization and an adaptive search algorithm that is more robust than previously described algorithms. Previous image processing approaches to geomorphological feature extraction from DEMs demonstrated the potential for feature-based approaches (Toriwaki and Fukumura 1978, Band 1986b, Bennett and Armstrong 1996). Recent developments in feature-based terrain analysis (Liang and Mackay 1997, Mackay and Band 1998) intelligently select algorithms based on feature type. However, feature-based approaches alone cannot handle highly variable topography and the need for a great many input parameters makes them inefficient in large watersheds. The approach presented here overcomes the need for excessive parameterization, by addressing the underlying problem of low signal-to-noise in relatively flat areas on DEMs. The breadth-first search algorithm presented here provides such an adapting mechanism, but does so without the need for *a priori* definition of object parameters. This new model preserves as much hydrologically significant information as is available in the DEM.

An important difference between depth-first searching and breadth-first searching needs discussion. In convergent topography, wide patches are formed using depth-first search, but near parallel flow lines are formed by the breadth-first search algorithm. This is consistent with the gradual reduction in signal-to-noise, which requires the algorithm to follow the trend in flow over a larger area. In wide valley bottoms this tends to produce near -parallel flow paths that are differentiated by a weak topographic signal. On a perfectly flat surface the breadth-first search produces parallel flow lines in the direction in which the search is initiated, as illustrated in figure 4. In contrast a depth-first search algorithm will degenerate into a simple space-filling curve that produces a single path for the whole flat surface.

Recently, Garbrecht and Martz (1997) presented an approach to resolving flow through flat areas. Their method is similar to the one presented here in that they adaptively search outward and look for drainage trends within the DEM. It differs in that they require some criteria to determine when to stop the search outward within the flat area, whereas the breadth-first search algorithm presented here requires no such criteria. In addition, the approach here uses a single algorithm for both flat

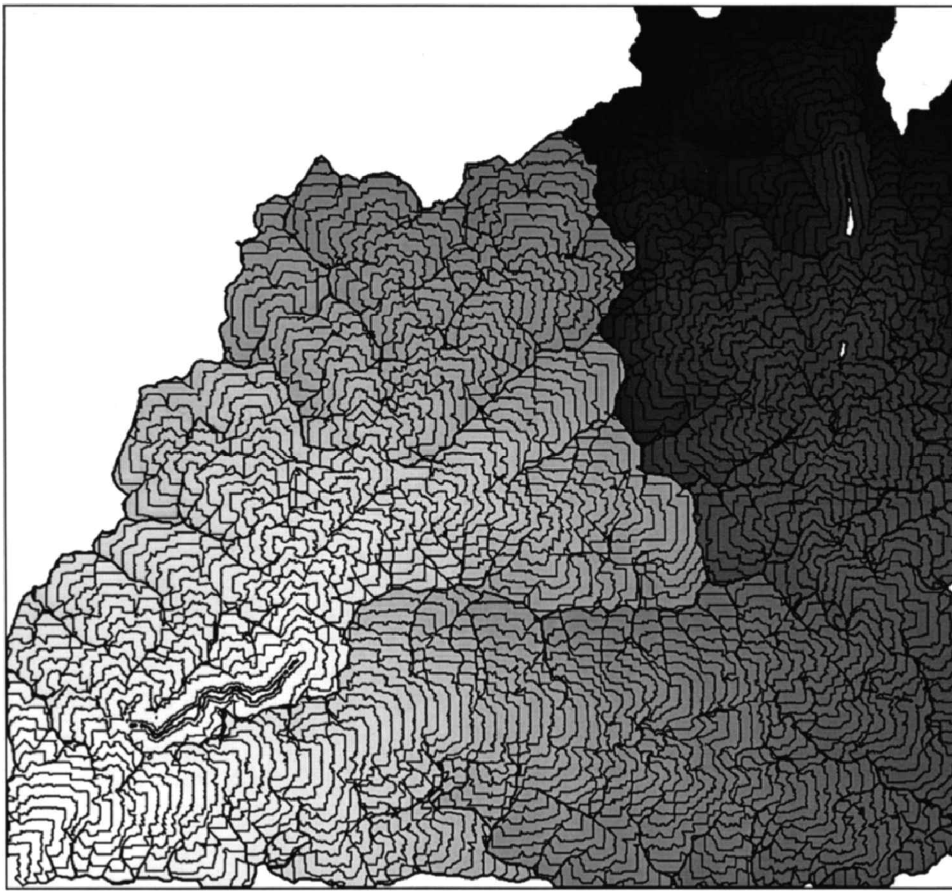

Figure 9. Animation of the advancing front line of the breadth-first search. The lighter tones indicate earlier stages of the search, while darker tones represent later stages of search. Superimposed in the image are snapshots of the position of the advancing front line at every 12 iterations. This figure shows that water bodies act as pour points around which concentric search neighbourhoods are formed. It also shows how preferential flow is formed in wide valley bottoms, such as near the lower edge of the image. The front line in these relatively flat area tend to be concentric arcs, which form convergent flow lines in the downstream direction.

and steep areas on the DEM, and so there is less chance of ambiguity in determining which algorithm to use as the search enters a transitional part of the landscape.

6. Conclusions

With the increased application of GIS in hydrologic modelling there is a growing need for improved compatibility between the spatial representation provided by GIS and the process representation provided by models. We argued earlier that the representation of watersheds within a GIS should more closely follow processes, by explicitly recognizing hydrologic features. For example, lakes, wetlands, and large floodplains are typically viewed as problem areas for watershed extraction and representation, and yet they are salient features of most landscapes in which hydrologic studies occur. We have shown that useful information can be gained from these

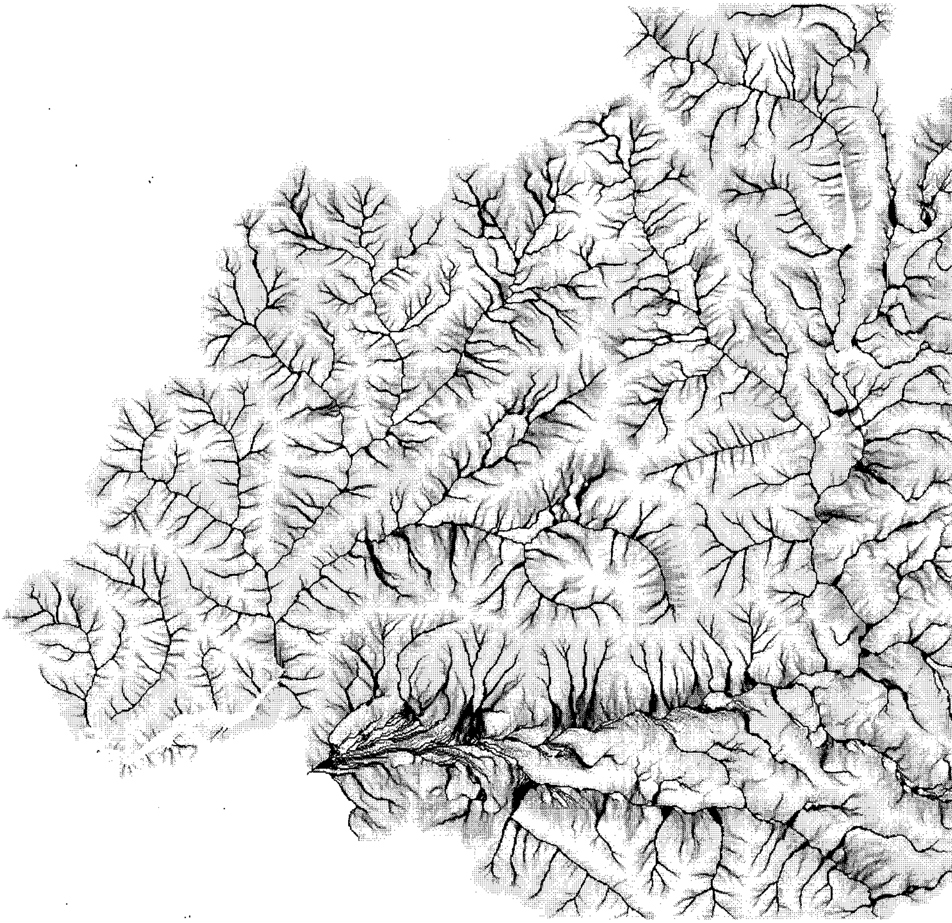

Figure 10. Fractional (F8) flow paths for two watershed areas at the Oregon site. F8 fields are a primary input to topographic indices, which are used in many hydrologic models.

areas when a combination of feature-based rules and more robust search algorithms are combined. The adaptive breadth-first searching algorithm presented here improves upon the traditional depth-first searching algorithms in finding clean, realistic flow paths in low relief areas of DEMs. When coupled with feature-based global optimization, it derives flow path and up-slope area fields from DEMs of various source data types without the need for parameter tuning by an end-user. This demonstrates that robust and easily generalizable approaches to watershed extraction and representation can be incorporated into a GIS framework.

A motivation for improving GIS-based terrain analysis tools is the need for spatial fields for input to hydrologic models of large spatial large extent, such as watersheds of order $10^3\,km^2$ or larger. Tools that require considerable parameter inputs or modification to be adapted to different parts of the landscape are inappropriate for large watershed studies at even moderate resolutions. The tools presented in this paper are appropriate for handling large watersheds with lakes, reservoirs, large flood plains, wetlands, and upland flat areas. In addition, by treating these hydrologically unique parts of the landscape as features directly improves the

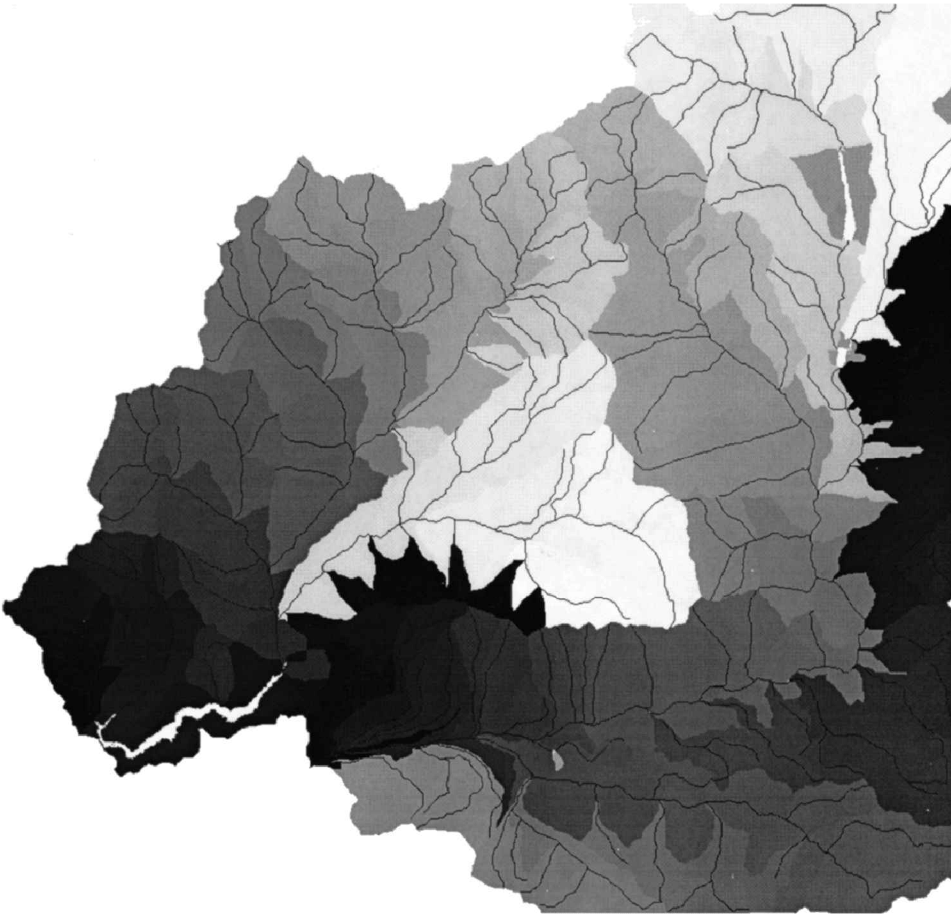

Figure 11. Sub-catchment partitions and stream lines for two watershed areas at the Oregon site. These partitions are primary inputs to many hydrologic model, as they represent closed hydrologic systems with well-defined boundaries.

development of databases to support hydrological modelling. An important consideration for future work in this area is to better understand the sensitivity of hydrologic models to the spatial representation provided by the GIS. More effort is needed in understanding how feature classification and flow path algorithm selection within GIS affect model design and implementation.

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