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Characterisation of valleys from DEMs

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Abstract: Valleys represent an important landscape feature for a number of environmental processes. However, the number of methods to reliably characterise them from digital elevation models (DEMs) is limited. We have recently developed a method to characterise fuzzy memberships of a set of morphometric features from DEMs at both single and multiple operational scales, using only the parameters of a quadratic function fitted to the elevation values within a moving window (Wang et al., in press). One of the morphometric features identified is multi-scale valleyness (MSV). In this paper we demonstrate the utility of the MSV using a small catchment near Canberra, ACT, Australia, as an example. The MSV results are compared against two flow accumulation algorithms (D8 and D∞) and the Multi-resolution Valley Bottom Flatness (MrVBF) index, each representing alternate approaches for characterising valleys. The results indicate that MSV effectively characterises valley areas from DEMs, with its reliability being negatively correlated with terrain complexity. The areas identified overlap with those of the other methods assessed, but also include areas not identified by these methods. The MSV approach represents a potentially useful tool for environmental modellers who need to identify valleys from DEMs.

Keywords: *Digital Elevation Model (DEM), Terrain Analysis, Spatial Analysis, Morphometric Features, Valleys*

1. INTRODUCTION

Valleys are an important morphometric landscape feature for environmental modelling. For example, they are zones of transport for many materials, particularly fluxes of sediment and other entrained materials (Whiteway et al., 2004), they represent zones through which cold air drainage moves and provide shelter from winds blowing across the valley axis. The characterisation of valleys from DEMs is an important step in environmental, hydrological and ecological modelling.

There are a number of methods to identify morphometric features from elevation data stored in Digital Elevation models (DEMs) (see Wang et al., in press). Common examples are focussed on peaks and pits, and are typically based on a set of rules that describe the shape of the terrain surrounding a point. However, there are comparatively few methods available by which one can automatically identify valleys. This is due in part to complexity. Valleys can take a large variety of forms, from broad and flat with a low along-valley slope to long and thin with a steep along-valley slope. It is therefore difficult to define a set of rules that can identify such variety.

Two current approaches to identifying valleys are to use flow accumulation indices to identify channel networks (e.g. Matsunaga et al., 2009) and hillslopes from which valleys can be inferred, or to use the Multi-resolution Valley Bottom Flatness index (MrVBF; Gallant and Dowling, 2003), which is intended to identify flat valley bottoms. These methods are very useful. However, they have been defined for specific uses, not for the general case of identifying valleys.

Recently we have developed a method of extracting a set of morphometric features from DEMs that does not depend on complex rule sets (Wang et al., in press). The method is based on fitting a quadratic surface to the elevation values in the DEM, from which indices are derived to describe the fuzzy memberships of the sets of peakness, pitness, passness, ridgeness and valleyness. The method can be applied across multiple operational scales and reduces the need for complex rule sets.

In this paper we demonstrate the utility of the multi-scale valleyness index (MSV) defined by Wang et al. (in press). The MSV results are compared against two flow accumulation algorithms (D8 and D∞) and MrVBF.

2. METHODS

We now describe the general principles of the four methods used, and then the specific analyses used in the comparison.

2.1. Flow accumulation algorithms

Two flow accumulation algorithms are used in this research, D8 (O'Callaghan and Mark, 1984) and D∞ (Tarboton, 1997). Both algorithms produce estimates of the upslope hydrological contributing area above a cell in a raster DEM. D8 models only converging flow and allocates all of the flow through a cell to its steepest downslope neighbour. D∞ models flow dispersal and convergence, with flow allocated on a weighted basis to two downslope neighbours.

2.2. MrVBF

The MrVBF algorithm (Gallant and Dowling, 2003) works on raster DEMs. The Valley Flatness (VF) at a single scale is calculated as a function of (1) the local topographic position of a cell within a moving window and (2) the slope of a 3x3 cell window. A cell is part of a flat valley when it is locally low and has a low slope. Fuzzy VF values for multiple resolutions are calculated by resampling the DEM to increasingly coarse resolutions and repeating the procedure. The MrVBF index is then a weighted combination of the individual VF values, with those VFs less than 0.5 considered as ridges and excluded.

The main potential issue with the MrVBF algorithm is that it achieves a multi-scale result by using multiple resolutions, rather than multiple operational scales. The coarser resolutions obtained by resampling the original DEM will reduce the terrain information of the original DEM, although such smoothing can be desirable in some cases.

2.3. The morphometric characterisation of valleys

Details of the morphometric characterisation system are given in Wang et al. (in press). In summary, the method uses least squares regression to fit quadratic surfaces of the form to the elevation values within a set of moving windows ($z = f(x,y) = Ax^2 + Bxy + Cy^2 + Dx + Ey + F$). These surfaces are then identified as elliptic, parabolic or hyperbolic paraboloids, and are rotated such that the axes are parallel to the x and y axes to simplify later calculations. The centre point of an analysis window is defined as a member of a morphometric set based on the position of the axes of the paraboloid relative to the window, with four cases being specific to valleys (Figure 1). Single Scale Valleyness (SSV, the membership of the fuzzy set of valleyness at a single scale) is calculated as the complement of the distance of the centre point from the axes divided by the radius of the analysis window. Multiscale valleyness (MSV) is calculated using a weighted combination of SSV values over a set of input scales.

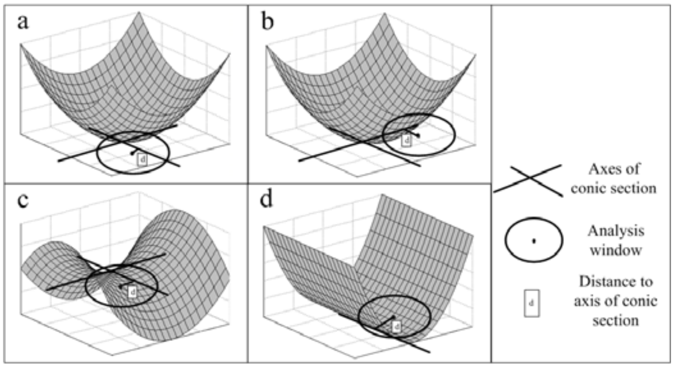

Figure 1. Morphometric identification of valley points is based on an analysis of the mathematical shape of the local quadratic surface and its positional relationship with the analysis window. Valley candidates are identified by four cases based on the intersection of the axes defined by a conic section: (a) two axes of a concave-up elliptic paraboloid, (b) one axis of a concave-up elliptic paraboloid, (c) the concave-up axis of a hyperbolic paraboloid, (d) the axis of a concave-up parabolic paraboloid. The fuzzy membership of the set of valleyness is based on the distance from the centre of the circular analysis window to the nearest axis, relative to the window's radius.

The least squares approach has two key advantages. First, the R^2 goodness of fit statistic can be calculated as an estimate of the reliability of the index at each scale. Second, the morphometric parameters can be calculated for any location rather than only where there are sample values. This is a property shared with other moving window regression approaches (Fotheringham et al., 2002) and means that the method can be applied to DEMs of any data structure so long as the data can be extracted and used in the least-squares fitting.

2.4. Analyses

A DEM of the Dunns Creek catchment near Canberra, ACT (35°26'30S, 149°8'30E, Figure 2) was used for the analyses. The DEM was interpolated from spot heights, contour data (5 m interval) and channels digitised from the ACT 1:10,000 scale planning series maps. The interpolation used the ANUDEM algorithm (Hutchinson, 1989), implemented in the TopoGrid Tool in ArcGIS Workstation version 8. The cell resolution is 10 m.

D8 and D∞ were calculated using the TauDEM extension for ArcGIS (http://hydrology.neng.usu.edu/taudem).

MrVBF was calculated using an Arc Macro Language (AML) tool running on ArcGIS Workstation 9.2, provided by Dr. John Gallant from CSIRO Land and Water, Canberra, ACT, Australia. According to the algorithm, the first step uses a 3-cell radius window based on the finest resolution; the second step uses a 6-cell radius window based

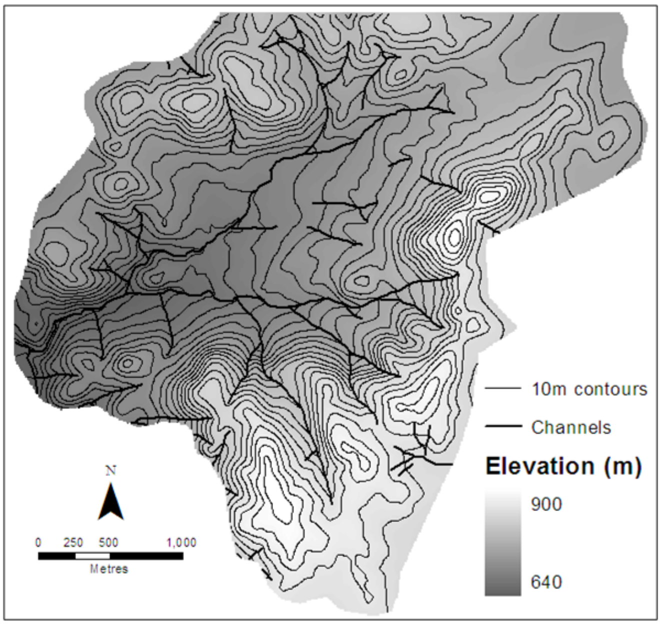

Figure 2. The Dunns Creek catchment (35°26'30S, 149°8'30E) has an elevation range of 260 m with two main valleys converging near its outlet at the south-west. Steep ridges define the edges of the catchment in the north and south, with a broad saddle area in the north-east. Drainage lines are discontinuous in the upper parts of the catchment.

on the finest resolution; and the radii of the remaining steps are all 6 cells with the reduced resolution DEM smoothed by a 3 by 3 cell window from the preceding step. The AML script provided used six steps but was edited to use only four, as the fifth and sixth resampling steps would potentially introduce large edge effects for the DEM used here. The scales of this four step MrVBF process correspond to windows of 3, 6, 18 and 54 cells radius.

MSV and the associated R^2 values were calculated using UNSWDEM software (Wang et al., in press). Four operational scales of radius 3, 6, 18 and 54 cells were used so that the MSV analysis windows corresponded to those used for the MrVBF calculations. The MSV value for each location was calculated from the SSV values using a linear power shape function with shape parameter of 1 and user weights of 1, 2, 4 and 8 for each scale respectively. The selection of weighting functions has been explored for this DEM by Wang et al. (in press), with limited effect being observed for the simple valley forms.

$$MSV = \frac{\sum SSV_{r_i}^{w_i}}{\sum w_i} = \frac{SSV_3^1 + SSV_6^2 + SSV_{18}^4 + SSV_{54}^8}{1+2+4+8} \tag{1}$$

where window radius $r_i \in \{3,6,18,54\}$ and weight $w_i \in \{1,2,4,8\}$.

There are no reference data to define which locations are valleys in this data set. In this case the results are compared against the drainage lines and elevation contours. Differences between the methods were assessed visually using scatter plots and numerically using Pearson's r correlation coefficients. The D8 and D∞ results were adjusted for the correlation coefficient calculations using a log10 transform to reduce the effect of their right skewed distributions.

3. RESULTS

The D8 and D∞ algorithms characterise valley centre lines from DEMs (Figure 3). They work well for identifying first and second order catchments, but not higher order catchments. They do not characterise valleys as areas, especially the single flow direction algorithm D8. Although D∞ uses multiple flow directions, the high contributing area values still only appear in a narrow area around the channels and show a sharp lateral decrease away from those areas.

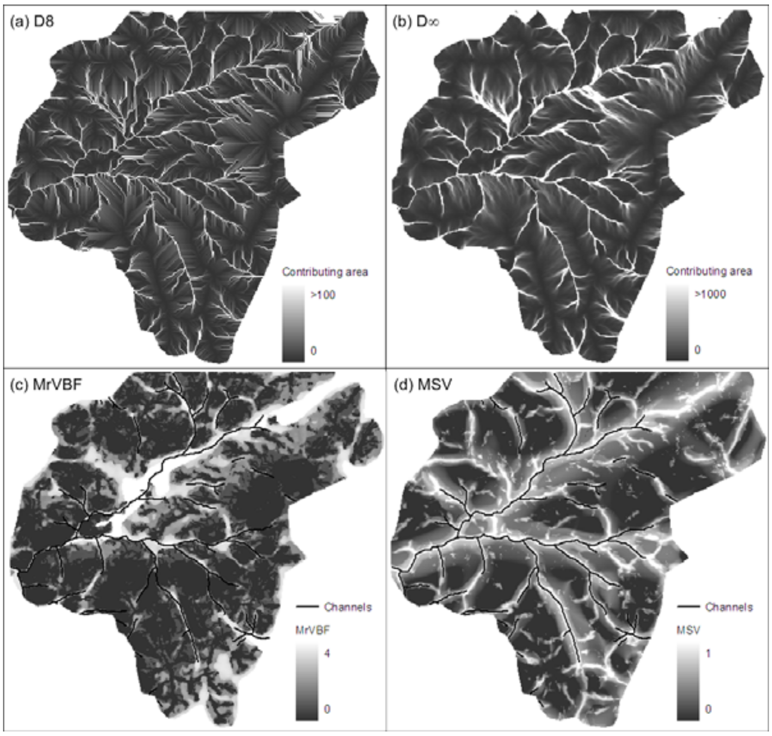

Figure 3. Plots of the D8, D∞, MrVBF and MSV results.

The MrVBF results (Figure 3) show broad areas of high values, and thus identify valley areas. The digitised channels are in the centre of these high value areas, indicating that the algorithm does well for characterising valleys from DEMs. These areas are also concentrated in the areas for which it was developed. For example, a large area with high MrVBF values occurs in the middle of the valley area, where the topography is comparatively flatter than the higher and lower parts of the catchment. However, the MrVBF algorithm does not identify the valley areas in the steeper first and second order sub-catchments, nor the steep, narrow valley near the catchment outlet.

The valley areas are clearly identifiable across the catchment in the MSV results (Figure 3). The digitised channels coincide with the high MSV value areas, and the MSV index identifies valleys at all catchment orders. The broad terrain features of the catchment from the broader scales are well represented without losing terrain details from narrower scales. The large valley in the middle of the study area is well portrayed by high MSV values, while the local ridges of the small knolls in the valley area can also be clearly observed by the relative variation of MSV values. Numerically, the MSV values are also distributed across the range 0 to 1 (Figure 4), reflecting the mixture of valley and ridge cells in the study area.

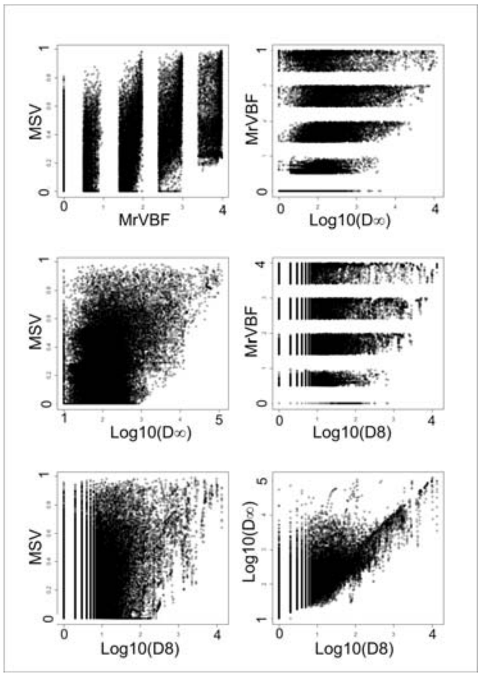

Figure 4. Scatter plots of each pair of MSV, MrVBF, D∞ and D8 algorithms. The gaps in the MrVBF plots are due to the exclusion of values less than 0.5 in each component VF.

The MSV results are weakly positively correlated with the D8 and D∞ results (Table 1, Figure 4). The correlation with D8 is 0.202, and with D∞ is 0.235. MSV is more correlated with MrVBF, although the correlation is still not strong (0.557). MrVBF and the two global algorithms are also only slightly positively correlated, being 0.183 for D8 and 0.159 for D∞. D∞ and D8 are strongly positively correlated with each other (0.747). The banding in the MrVBF plots is because ridges are excluded in the method.

Table 1. Correlation coefficients of the four algorithms

	MSV	MrVBF	D∞	D8
MSV	1.000			
MrVBF	0.557	1.000		
D∞	0.235	0.183	1.000	
D8	0.202	0.159	0.747	1.000

4. DISCUSSION

The D8, D∞, MrVBF and MSV approaches characterise valleys using different principles and perform accordingly. The flow accumulation algorithms perform well when valley centre lines are needed. However, if the landscape is to be classified into different geomorphic zones then MrVBF and MSV are more effective. MrVBF performs well when characterising valley bottoms where the terrain is flat and low, for which it was designed. In contrast, MSV characterises valley areas from DEMs regardless of whether the terrain is flat or not. MSV is therefore more appropriate than MrVBF for characterising valleys in steep areas, and better than the flow accumulation indices when valley areas and not centre lines are needed.

The MSV approach has the added advantage that some estimate of the reliability of the results can be obtained using the R^2 surfaces for each individual analysis scale (Figure 5). From this one can infer that the results of the 3 and 6 cell radii fit well across the whole study area, the 18 cell radii windows work well for most locations, with a notable exception being the small knoll in the lower part of the catchment (immediately above the confluence of the main channels). By the 54 cell scale the fit is less reliable as the quadratic function is identifying the broad elevation trends but not the finer detail. This can also be observed in the single scale valleyness plots (Figure 6).

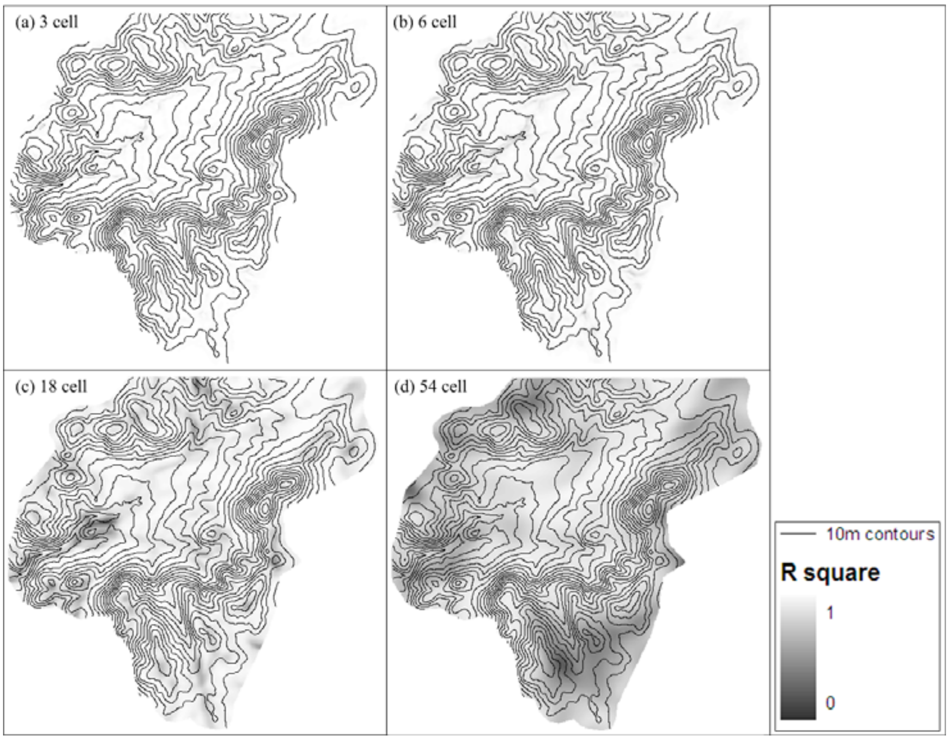

Figure 5. R^2 values for each SSV index. Window sizes are radii.

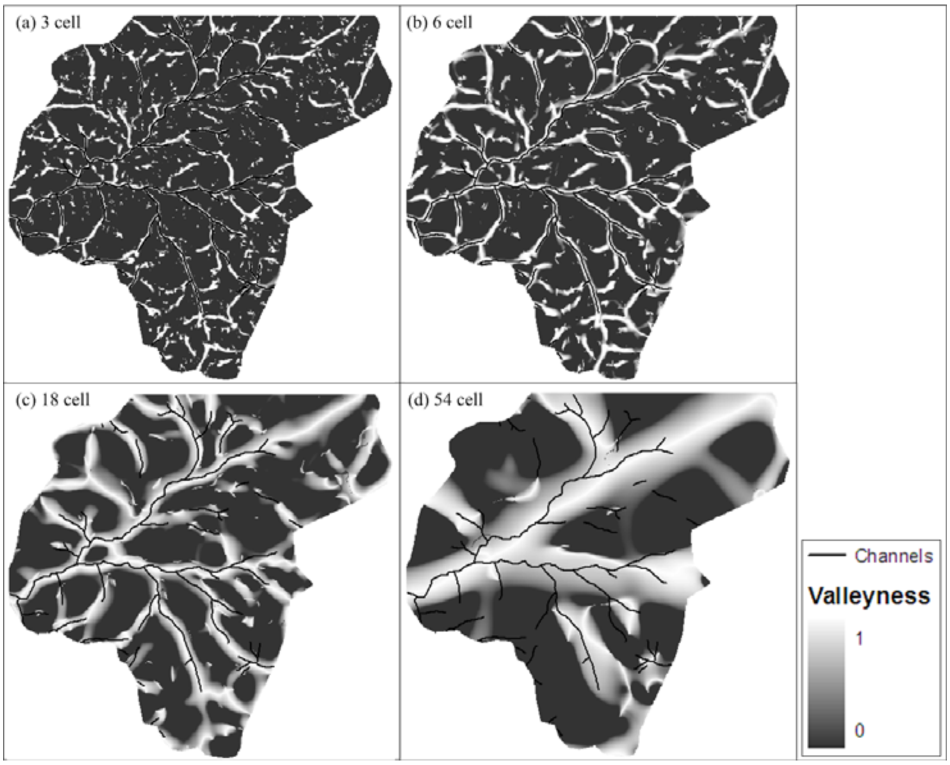

Figure 6. SSV values at the four operational scales used.

One point to note about the MSV is that it does not differentiate between valleys of different shapes, for example those that are broad and flat versus those that are steep and narrow. However, the use of the quadratic approach means that other geomorphometric indices can be derived to describe morphological properties for individual scales using the parameters of the quadratic surface. Two examples are longitudinal and cross-sectional curvatures (Wood, 1996). Specific types of valleys, for example flat valleys as identified by MrVBF, could be identified by first identifying candidates using the MSV index, followed by more specific analyses using geomorphometric indices.

5. CONCLUSIONS

The results indicate that the MSV approach effectively characterises valley areas from DEMs, with its reliability being negatively correlated with terrain complexity. The areas identified overlap with those of the other methods assessed, but importantly these areas include those not identified by the other methods. The MSV approach represents a potentially useful tool for environmental modellers who need to identify valleys from DEMs.

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