

Fuzzy delineation of drainage basins through probabilistic interpretation of diverging flow algorithms

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ABSTRACT

The assessment of uncertainty is a major challenge in geomorphometry. Methods to quantify uncertainty in digital elevation models (DEM) are needed to assess and report derivatives such as drainage basins. While Monte-Carlo (MC) techniques have been developed and employed to assess the variability of second-order derivatives of DEMs, their application requires explicit error modeling and numerous simulations to reliably calculate error bounds. Here, we develop an analytical model to quantify and visualize uncertainty in drainage basin delineation in DEMs. The model is based on the assumption that multiple flow directions (MFD) represent a discrete probability distribution of non-diverging flow networks. The Shannon Index quantifies the uncertainty of each cell to drain into a specific drainage basin outlet. In addition, error bounds for drainage areas can be derived. An application of the model shows that it identifies areas in a DEM where drainage basin delineation is highly uncertain owing to flow dispersion on convex landforms such as alluvial fans. The model allows for a quantitative assessment of the magnitudes of expected drainage area variability and delivers constraints for observed volatile hydrological behavior in a palaeoenvironmental record of lake level change. Since the model cannot account for all uncertainties in drainage basin delineation we conclude that a joint application with MC techniques is promising for an efficient and comprehensive error assessment in the future.

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Software availability

Program title: TopoToolbox

Developer: Wolfgang Schwanghart

First available: 2009

Source language: MATLAB

Version: 1.06

Requirements: MATLAB R2011b, Image Processing Toolbox

Availability: TopoToolbox is open source, available free of charge and can be downloaded on <http://physiogeo.unibas.ch/topotoolbox/>

1. Introduction

The assessment of uncertainty has been identified as one of the main challenges for geomorphometry (Wood, 2009) that becomes an increasingly pressing issue. Errors are inherent in digital

elevation models (DEM) and have a significant influence on the reliability of products derived from them (Fisher, 1998; Fisher and Tate, 2006; Hengl et al., 2010; Vaze et al., 2010). This is particularly true for the new generation of DEMs that have been made available with high spatial resolutions falling below one meter since it remains largely unclear whether the high-resolution equates to high accuracy (Temme et al., 2009).

DEM elevations differ from what we measure in the field. Measurement devices such as remote sensors have limited accuracy and discretization to a gridded representation requires interpolation and generalization (Heritage et al., 2009). Moreover, DEM derivatives may be erroneous due to the precision of calculation techniques (Florinsky, 1998; Raaflaub and Collins, 2006). High-resolution, LiDAR DEMs contain new sources of uncertainty generated by the intricate process of filtering vegetation or the obstruction of digital flow paths by man-made landscape features such as bridges. In addition, high-resolution DEMs capture more and more small-scale and possibly short-lived geomorphological features such as channel bars. While repeated retrieval of such DEMs enable the detailed assessment of temporal development of topography they may limit the DEMs applicability to pre- and post-survey situations.

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Uncertainty has been assessed using analytical error propagation techniques or numerical Monte-Carlo approaches. While analytical techniques may be employed to assess the accuracy of the initial data and precision of a calculation technique, they are usually restricted to local topographic variables such as slope and curvature. Uncertainty in non-local topographic variables such as viewsheds or specific catchment area, however, is far more difficult to assess analytically (Fisher, 1998; Florinsky, 1998) and thus, Monte-Carlo (MC) approaches are used to study error propagation (Oksanen and Sarjakoski, 2005; Raaflaub and Collins, 2006; Temme et al., 2009; Hengl et al., 2010). Such approaches, however, are computationally intensive to obtain stable error bounds (Hengl et al., 2010).

Here we introduce a new analytical model to quantify and visualize uncertainty in drainage basin delineation that is based on the assumption that multiple flow directions (MFD) represent a discrete probability distribution of non-diverging flow networks. The Shannon entropy is used as index to quantify the uncertainty. Following a short introduction into this measure of uncertainty, we present the governing equations to derive it from DEMs, outline the software implementation and then provide an example of fuzzy drainage basin delineation for visualizing and interpreting the hydrological contributing area of lake Ugii Nuur, Mongolia.

2. Shannon entropy

Understanding the influence of errors in DEMs on drainage basin delineation requires a way to quantify flow path variability through an index that captures uncertainty. An entropy-based index derived from Shannon's information theory (Shannon, 1948) has long been used in different disciplines as measure of disorder, unpredictability and diversity. Most commonly, it is found in ecological literature referred to as 'Shannon Index' or H of species diversity (Spellerberg and Fedor, 2003; Beck and Schwanghart, 2010) where it describes the entropy of a community composed of N species and is defined as the weighted mean of the quantity of entropy associated with the single species:

$$H = - \sum_{i=1}^N p_i \log p_i \quad (1)$$

where $p_i \in [0; 1]$ is the relative abundance of the i th species such that $\sum_{i=1}^N p_i = 1$. H is low if one species dominates the species distribution and reaches a maximum if all species are present in equal proportions p_i (Fig. 1). Here, H may be considered as a measure of uncertainty about the relative abundances of species.

In image analysis, entropy is a local and global statistical measure for the randomness and texture of an image (Gonzalez et al., 2003). Entropy is used in the context of terrain analysis as indicator for terrain roughness (Franklin, 1987) and measure for the quality of landform classes derived from fuzzy classifications (e.g. Wood, 1996; Burrough et al., 2000; Fisher et al., 2004). The Shannon Index can be transferred to flow path variability in a way that it describes the uncertainty of a location in the DEM to drain to a specific outlet. Most locations are clearly associated with a specific outlet. However, a deterministic allocation may be impossible for locations on watersheds or landforms where diverging flow paths prevail.

3. Fuzzy watershed delineation

The derivation of fuzzy drainage basins from DEMs can be written as a set of linear equations based on the MFD matrix \mathbf{M} as introduced by Schwanghart and Kuhn (2010). \mathbf{M} is associated with a DEM with n cells linearly indexed from $i = 1, 2, \dots, n$. \mathbf{M} has n rows and columns and is sparsely populated. Non-zero entries in \mathbf{M} in

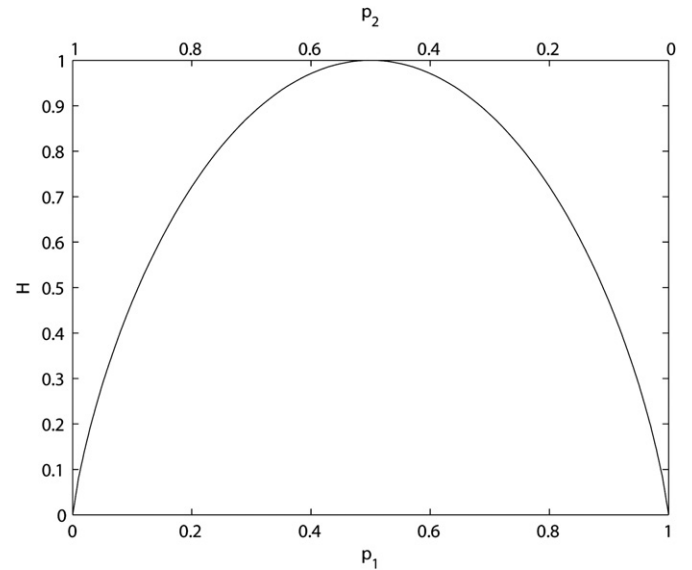


Fig. 1. The Shannon Index H as a function of the probabilities (p_1, p_2) of two variables.

row i and column j contain the proportion $p(i, j)$ of water transferred from cell i to cells j in i 's Moore neighborhood in the DEM (Schwanghart and Kuhn, 2010). The way the proportions are calculated depends on the flow routing algorithms. The MFD algorithm applied here, takes all lower neighbors of cell i and $p(i, j)$ is proportional to the slope between i and j (Freeman, 1991). In a network model, a non-zero proportion refers to an edge between node i to j . \mathbf{M} is a stochastic matrix since values in each row add up to unity if cell i has at least one downslope neighbor. Otherwise, the sum along rows is zero. The maximum number of non-zero entries in \mathbf{M} in row i is eight. In this case, i refers to a topographic peak draining to all of its eight neighbors.

Fuzzy watersheds are based on the assumption that the proportions given in the MFD matrix describe the probability that water is routed from node i and j (Fig. 2a). The single flow direction (SFD) matrix may be regarded as the most probable realization or expected network of very many possible, non-diverging flow networks. Thus, other realizations of non-diverging flow networks can be computed by random sampling each node's edges with probability $p(i, j)$ given by the multiple flow direction matrix.

In a deterministic, non-diverging flow network cells are easily identified that drain to a specific pour point (Figs. 2b and 3a). If we define each sink cell in the DEM (each cell without downstream neighbor) as pour point s , each cell i can be definitely assigned to a single s by $p(i, s) = 1$ if it drains into s (Fig. 2b). Otherwise, $p(i, s) = 0$. The set of cells i_s for which $p(i, s) = 1$ form the drainage basin of s .

In contrast, the cells belonging to fuzzy drainage basins are characterized by the probability $p(i, s) \in [0; 1]$ of draining into sink s (Fig. 3b and c). Here, flow paths may lead from a cell i to more than one sink s . The probability that i drains in s is the sum of probabilities that the downstream successors j of i drain into s times the probabilities that i drains into j . If interpreted deterministically, $p(i, s)$ would correspond to the areal fraction that a node contributes to a certain outlet. This can be written as linear system of equations

$$p(i, s) = \sum_j (p(j, s) \cdot p(i, j)) \quad (2)$$

Together with the condition that the probability that s drains into s is one

$$p(s, s) = 1 \quad (3)$$

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