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Integration of fuzzy logic and image analysis for the detection of gullies in the Calhoun forest using airborne LiDAR data

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Introduction

This work is aimed to evaluate the combination of different simple morphometric indices to characterize the morphological properties of gullies in a fuzzy logic framework. Such algorithms and methods are applied to the Calhoun CZO where many gullies have been observed and mapped in previous works and where a very high resolution LiDAR DEM is available. The entire procedure tries to successfully automate gully mapping and the resulting estimates of erosion patterns, which characterize the Calhoun area. The following objectives may be then identified:

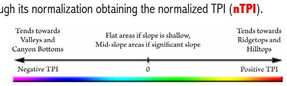
- developing and assessing an automated procedural chain of different algorithms to detect gullies based on their morphological characteristics retrieved by LiDAR DEM, and
- developing and evaluating a method to measure main characteristics of gullies (i.e depth and volume).

Indices used as gully markers

Gully bottom index

TPI Topographic position index *(continuous variable)*

The TPI (Gallant and Wilson, 2000) is simply the difference between a cell elevation value and the average elevation of the neighborhood around that cell. Positive values mean the cell is higher than its surroundings while negative values mean it is lower. Here the TPI has been slightly modified through its normalization obtaining the normalized TPI (**nTPI**).



Gully boundary indices

c_{max} Maximum Profile Curvature (*continuous variable*)

The DEM surface is approximated to a bivariate quadratic function in the form (Evans 1979):

$$Z = ax^2 + by^2 + cxy + dx + ey + f$$

where x, y, and Z are local coordinates, and a to f are quadratic coefficients, assessed using elevation in kernel size of n x n.

Evans (1979) suggests two measures of minimum (concavity) **and maximum curvature (convexity)**. **Maximum curvature** has been adopted as index of gully edge since landforms as the gullies correspond to convex slope breaks forming ridges and these are related to surface convexity.

$$C_{\max} = -a - b + \sqrt{(a-b)^2 + c^2}$$

Here a multiple-scale parameterization proposed by Wood (1996) by generalizing the calculation for different window sizes, is used.

MinMax index *(continuous variable)*

MinMax is a focal map algebra function defined by Gallant and Wilson (2000) as ER (Elevation Range). This filter calculates the difference between the maximum and minimum values of elevation *z* present in a moving kernel, with size equal to α, and stores the result into the central pixel of this kernel. This continuous index has been used since high values may highlight the presence of strong discontinuities in the terrain surface (i.e. gully edge).

Vosselman index *(Boolean variable)*

This index is the outcome of a filter derived by Vosselman (2000) to detect anomalies in the elevation of a LiDAR dataset due usually to the pulses reflected by buildings, trees, and many other objects on top of the ground surface.

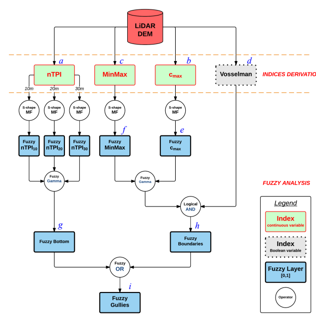
Here this filter, implemented in GRASS GIS, has been used to detect the gully boundaries as anomalies of the terrain.

Procedural chain – Fuzzy logic

The first step is relative to the four **indices derivation** (**nTPI**, **c_{max}**, **MinMax** and **Vosselman index**). All these indices require the definition of a scale (i.e. the size α or the radius *r* of the kernel). Particular attention has been paid to the definition of this support scale.

These indices are usually used in a typical Boolean approach, which consists in defining thresholds for each of the different indices, assigning value one (presence of gully feature) to all the pixels which are above (or under) the threshold and value zero (absence of gully feature) to all the pixels which are under (or above) the threshold and merging the information coming from each single index.

Here an approach alternative to the classical Boolean one has been developed using the **fuzzy logic approach**. This approach allows to combine the different indices and to derive a map which provides a sort of probability that each single pixel is part of a gully.

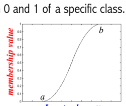


Fuzzy logic can be considered as a superset of conventional (i.e. Boolean) logic that has been extended to handle the concept of **partial truth**, i.e. truth values between "completely true" and "completely false".

The key point of fuzzy logic is to map an input variable to an output variable using, as primary mechanism, a list of if-then statements called rules, through a complex process called fuzzy inference. Fuzzy inference is a method that interprets the values in the input variable and, based on some set of rules, assigns values to the output variable.

This is carried out through a **membership function (MF)** that is a curve that defines how each point in the input variable is mapped to a membership value (or degree of membership) between 0 and 1 of a specific class.

MEMBERSHIP FUNCTION S-SHAPE



$$f(x;a,b) = \begin{cases} 0 & x \le a \\ 2\left(\frac{x-a}{b-a}\right)^2 & a \le x \le \frac{a+b}{2} \\ 1 - 2\left(\frac{x-b}{b-a}\right)^2 & \frac{a+b}{2} \le x \le b \\ 1 & x \ge b \end{cases}$$

The fuzzy raster layers can be combined together using specific fuzzy operators (Bonham-Carter, 1994). Here two different fuzzy rules have been used: fuzzy gamma operator and the fuzzy union OR.

The **fuzzy gamma operator** is derived by combining fuzzy algebraic sum together with fuzzy algebraic product

$$\mu_{gamma} = \mu_{al,sum}^{\gamma} * \mu_{al,prod}^{1-\gamma} = \left[\prod_i^n \mu_i\right]^{\gamma} * \left[1 - \prod_i^n (1-\mu_i)\right]^{1-\gamma}$$

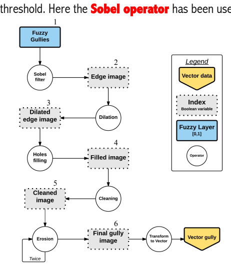
The **fuzzy union OR** provides output membership values are controlled by the maximum values of any of the input membership spatial layers, for any particular location.

The **gullies fuzzy map** is "cleaned" through the use of mode filter to remove single isolated pixels. Iterative buffer analysis allows for removing boundaries pixels "too far" (>10-15m) from bottom part and removing bottom pixels "too far" from boundaries pixels. All the procedure has been implemented in **GRASS GIS**.

Procedural chain – Image Analysis

The fuzzy layer showing the degree of membership to the class of gullies can be further using the techniques of **image edge detection**.

In order to detect edges in a image, there are many functions that look for places in the image where the intensity (i.e. pixel values) changes rapidly; in particular some functions look for places where the first derivative of the intensity is larger in magnitude than some threshold. Here the **Sobel operator** has been used.



The final outcome of Sobel operatore is usually a Boolean layer raster where many gaps in the lines surrounding the candidate gullies can be observed together with many small pixel clusters scattered in the landscape. These linear gaps and isolated pixel clusters can be removed using **morphological operators in image analysis** (Haralick et al., 1988; Haralick and Shapiro, 1992).

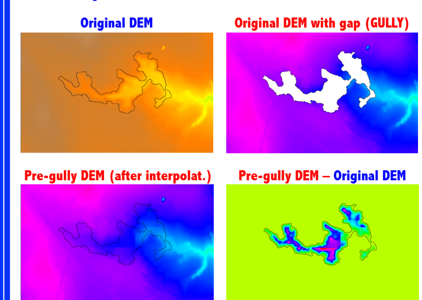
The most basic morphological operators are **dilation** and **erosion**.

Dilation, which combines two sets using vector addition of set elements, adds pixels to the boundaries of objects in an image, while **erosion,** which is the morphological dual to dilation and combines two sets using the vector subtraction of set elements, removes pixels on object boundaries. In this case the following sequence of dilation, erosion and filling algorithms have been implemented in **MATLAB** in order to improve the shape of the extracted gullies.

Gully volume assessment

Gully volume assessment is carried out, using an approach similar to that employed by Daba et al. (2003) and Evans and Lindsay (2010) but through a interpolation algorithm more complex than those used by these two works.

a) The creation of a buffer around the gully perimeter;
b) The transformation of pixel values within this buffer in points (x, y, z);
c) The creation of a "**pre-gully**" top surface (only for the area covered by the gully) using specific interpolation method (ANUDEM, Hutchinson, 1988; 1989) or RST (spline);
d) The calculation of the gully volume as difference between the "**pre-gully**" top surface DEM and the **original DEM**.



Volume assessment

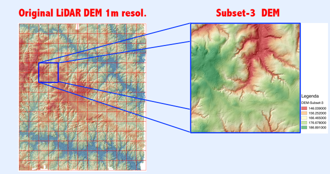
Category Number	Average in clump	Data Total	# Cells in clump	Centroid Easting	Centroid Northing	Total Volume
1	3.27m	44052	13478 m²	430544	3831799	44052.32

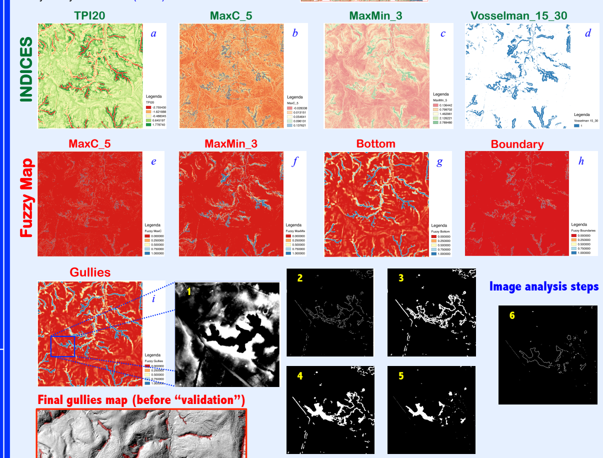
Total Volume = 44052.32 m²

Preliminary results

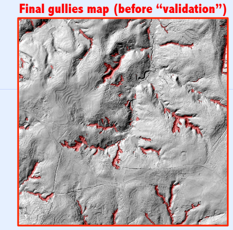
The LiDAR data was collected, through the CALHOUN CZO project., over 2 days (August 5, 2014 - August 6, 2014). DEM with 1m resolution was obtained for the total survey area of a 13 km x 15 km rectangle (195 km²) located at 40 km SE of Spartanburg, SC.

A first application of the proposed method has been carried out on a 2 km x 2 km area called **SUBSET 3** which encompasses one of the two gully system analyzed by James et al. (2007) – **COMP32 GULLY**.





Final gullies map (before "validation")



Ongoing activities

- Field survey to measure some gullies (DGPS Topcon)
- This data will be used to calibrate parameters of the procedural chains.
- Application of an alternative method to identify gullies based on GEOBIA (Blaschke et al., 2010).
- Comparison of two methods (pixel-centric vs. GEOBIA).

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