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

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Abstract

The entire Piedmont of the Southeastern United States, where the Calhoun Critical Zone Observatory (CCZO) is located, experienced one of the most severe erosive events of the last two centuries. Forested areas were cleared to cultivate cotton, tobacco, and other crops during the nineteenth and early twentieth century and these land use changes, together with intense rainfalls, initiated deep gullying. An accurate mapping of these landforms is important since, despite some gully stabilization and reforestation efforts, gullies are still major contributors of sediment to streams. Mapping gullies in the CCZO area is hindered by the presence of dense canopy, which precludes the identification through aerial photogrammetry and other traditional remote sensing methods. Moreover, the wide spatial extent of the gullies makes the identification and characterization of entire gullies through field surveys a very large and expensive proposition.

This work aims to develop a methodology to automatically detect and map gullies based on a set of algorithms and morphological characteristics retrieved by very high

resolution (VHR) imagery. A one-meter resolution LiDAR Digital Elevation Model (DEM) is used to derive different morphometric indices, which are combined by using spatial analysis methods and fuzzy logic rules, building up a tool able to automatically identify gullies. This spatial model has been calibrated using, as reference, the perimeters of two relatively large gullies that have been measured during a recent field survey. The entire procedure aims to provide estimates of gully erosion patterns, which characterize the entire CCZO area, and to develop an objective method to measure characteristic features of gullies (i.e., depth and volume).

1. Introduction

Agricultural practices are known to be very important causes of accelerated soil erosion. Among the different types of soil erosion, gully erosion can be considered as a form of accelerated erosion. Gullies are fairly steep-sided channels which experience ephemeral flows mainly during heavy or prolonged rainfall periods. The presence of significant gully erosive processes may affect soil productivity, restrict land use and lead to an increase of risk to infrastructure.

Poesen et al. (2003) highlighted that gully erosion is an important soil degradation process in a range of environments, causing considerable soil losses and producing large volumes of sediment. Moreover, gullies efficiently move runoff and sediment from uplands to lowlands and aggravate offsite effects of soil erosion. Gully erosion processes may significantly degrade soils and have detrimental effects on water quality and sediment discharge in a catchment. Data collected from different parts of the world by Poesen et al. (2003) highlight the dramatic importance of gully erosion processes; they show that the

associated soil loss rates may represent a range of 10% to 94% of the total sediment yield caused by water erosion (Poesen, 2011).

Some of the major causes of gully erosion can be related to inappropriate cultivation and irrigation, overgrazing, logging, road construction and urbanization. Other drivers of gully erosion are concentrated runoff from steep lands flowing into cleared drainage depressions, unstable soils in drainage lines, and elevated runoff caused by factors such as low levels of tree cover and poor soil infiltration (Daba et al., 2003; Valentin et al., 2005).

Identifying gullies requires a very precise definition of such landforms. Peasley and Taylor (2009) defined gully erosion as a process that causes the removal of soil through concentrated surface runoff and characterized by incised channels greater than 30 cm, and generally restricted to streams with order lower than three. Poesen et al. (2003) classified gullies as *permanent gullies*, *ephemeral gullies*, and *bank gullies*. *Permanent gullies* are channels deep enough (ranging from 0.5-25-30 m; Soil Science Society of America, 2001) not easily ameliorated with ordinary tillage practices; *ephemeral gullies*, which have smaller channels than permanent gullies, are initiated by concentrated flow and have channel erosion larger than rill erosion but less than classical gully erosion; and *bank gullies* are developed wherever concentrated runoff crosses an earth bank.

Morphometric characteristics of gullies including shape, size and growth pattern are influenced by soil factors such as erodibility and the occurrence of fragipans within the profile (Moore et al., 1988). Other influences are topography such as the upstream contributing area (Poesen and Govers, 1990), bed and slope steepness (Foster, 1986; Poesen and Govers, 1990; Poesen, 1993) and by agronomic practices. Even if some attempts

72 have been made to provide a systematic classification of such characteristics relative to the
73 different types of gullies and their controlling factors (e.g. topography, soil type, land use,
74 hydrology) in different environments, there is still no consensus on single definitions, and
75 many aspects of the classification of gullies remain quite vague (i.e. the distinction between
76 a large gully and an ephemeral river channel).

77 While gullies have been mapped through conventional field surveying, this task is an
78 intensive and expensive activity. Identifying the edges of relatively large gullies can be
79 difficult, even from in-situ observations. Accurate and spatially extensive information on
80 gully location and extent at an appropriate spatial scale is essential to take measures in
81 reducing sediment movement (Poesen et al., 2003).

82 The definition of gullies can be achieved in terms of morphological characteristics. Since
83 the most important source of quantitative morphometry is provided by *Digital Elevation*
84 *Models* (DEMs), they are a popular choice for mapping gullies. So far, one of the main
85 historical obstacles for using of DEMs for mapping gullies at landscape scale has been the
86 relatively low resolution that characterized past DEMs. The recent widespread availability
87 of *very high resolution* (VHR) imagery has drastically changed this constraint, leading to a
88 remarkable growth in the availability of terrain information with notable advantages over
89 traditional surveying techniques (Slatton et al., 2007), and providing a basis for the
90 development of new methodologies for analyzing Earth surfaces (Tarolli et al., 2009).

91 Among VHR products, the most promising data source for identifying gully systems is
92 airborne LiDAR data (Roering et al., 2013) because of its fine resolution, high accuracy (i.e.
93 submeter resolution) and its capability to derive bare ground surface topographic data by

94 automatically filtering vegetation and other objects on the surface (Tarolli, 2014). Extensive
95 LiDAR datasets are now available in several countries. Previous efforts have demonstrated
96 the ability of airborne LiDAR to accurately represent gully cross-sectional forms (Jackson et
97 al., 1988; Ritchie et al., 1994), to map the location of gully heads (Hancock and Evans, 2006),
98 and to characterize gully networks (James et al., 2007).

99 Different procedures have been developed to operate on these high resolution DEM data.
100 They can be roughly classified as a) *pixel-based* (or using *per-pixel approach*) and b) *object-*
101 *based* (i.e. using *object based image analysis - OBIA*). The former approach encompasses all
102 work based on the classical approach of map algebra where the pixel is the main spatial
103 primitive with a “*pixel-centric*” view typical of traditional remote sensing and GIS science
104 (Martinez-Casasnovas, 2003; James et al., 2007; Evans and Lindsay 2010; Perroy et al.,
105 2010; Baruch and Filin, 2011; Höfle et al., 2013; and Castillo et al., 2014); whereas the latter
106 approach is based on the analysis of spatial data based on the concept of the image object
107 (see Blaschke, 2010; Blaschke et al., 2014; Eustace et al., 2009; Shruthi et al., 2011;
108 Johansen et al., 2012; d’Oleire-Oltmanns et al., 2014).

109 One of the earlier efforts based on the *pixel-centric* approach is that of James et al. (2007)
110 who mapped gullies, and headwater streams of the Sumter National Forest (SNF) of the
111 South Carolina Piedmont (southeastern USA) under dense forest canopy using a 2 m
112 resolution LiDAR DEM. The authors did not propose a unified and automated method to
113 extract gullies from the DEM but rather demonstrated the use of the upstream contributing
114 area with fixed threshold in identify gullies by comparing it with other methods (i.e.
115 contour crenulations). However they suggested that the use of LiDAR DEM can
116 underestimate gully depths and overestimate widths because of shading of gully floors from

off nadir beam paths, or potentially because of removal of information during pre-processing of the LiDAR DEM.

Evans and Lindsay (2010) developed a pixel-based approach to extracting gully maps using a 2 m LiDAR DEM. A combination of areas of low difference from mean elevation and high positive plan curvature was used to detect the position of gullies. Moreover, the authors analyzed the effect of the kernel size of the indices, highlighting that the optimal size has to be greater or equal to the width of the gullies (i.e. 30 m for the study area). Gully depth was estimated for a particular grid cell by subtracting an estimate of 'pre-gully' elevation, obtained by a weighted linear interpolation method specifically derived by the authors, from the elevation of the grid cell in the LiDAR DEM.

An automatic GIS-based detection and delineation of gully channels has been proposed by Höfle et al. (2013) for a high altitude and remote cushion peatland in the Peruvian Andes, using a LiDAR DEM. The method combines breaklines detection and sink filling based on a hydrologically conditioned DEM (i.e. a DEM without sinks). This method is able, according to the authors, to delineate landforms even if gully bottoms have only partly been captured, due to topographic occlusion of the laser scan.

Castillo et al. (2014) implemented and tested an automated GIS-based procedure built on normalized topographic indices for gully mapping in Spain using topographic data of a variety of scales, ranging from the rill to the badland landscapes. The authors demonstrated that the joint use of normalized elevation and slope as detection variables and of other topographic variables for filtering purposes was an efficient and scale-independent approach for gully mapping. Since resolution plays an important role in the analysis of

139 DEMs and the accuracy of associated derivatives, the authors demonstrated that the
140 optimal window size of the normalized indices was in the order of twice the maximum
141 width of the gully.

142 While the performance of the traditional *pixel-based* approaches depends entirely on the
143 information of single pixels and the direct neighborhoods, the second group of methods,
144 based on the paradigm of *Object-based Image analysis* (OBIA or GEOBIA when the
145 GEOgraphical aspect is taken into account), still exploit pixel information but through a
146 procedure of pixels grouping. Additional features such as homogeneity of the region and
147 within-region variation can be addressed. The regions are typically generated through
148 using one or more criteria of homogeneity in one or more dimensions (d'Oleire-Oltmanns et
149 al., 2014).

150 Eustace et al. (2009) pioneered the detection of gullies based on the GEOBIA paradigm.
151 The authors used a semi-automated object oriented classification method to detect and map
152 gully extent and volume in eastern Australia. Although the method provided promising
153 results when compared to other VHR data sources, the study did not use field data to verify
154 the volumetric gully estimates.

155 Shruthi et al. (2011) presented an approach based on the use of 1m DEM derived from
156 the IKONOS satellite data. The DEM was hydrologically corrected using the software SAGA
157 (*System for Automated Geoscientific Analyses*) GIS to obtain terrain derivatives such as slope,
158 flow direction, specific catchment area and sub-watersheds, which were used, along with
159 the DEM, as input layers for OBIA. The approach was promising, as the method could

160 identify the finer gully edges within the complex gully system better than a manual
161 digitization method, which is highly subjective.

162 Following the work of Eustace et al. (2009), Johansen et al. (2012) applied object-based
163 approach for mapping the spatial extent and volume of gullies in northern Australia using
164 LiDAR DEM data from 2007 and 2010 with a spatial resolution of 0.5 m. Gully edges were
165 detected using a min/max filter with a 2D kernel size of 5 x 5. A complex procedure based
166 on a series of image segmentation was applied based on the DEM and slope layers to create
167 objects on both the outside and inside of the gullies, and to extract gullies from the DEM.

168 Finally, recent work by d'Oleire-Oltmanns et al. (2014) made use of four bands from the
169 QuickBird-2 satellite imagery (0.6 m resolution) instead of DEM, to detect gullies in the
170 region of Taroudannt, Morocco. After initial image segmentation, a hierarchical multi-scale
171 approach, with multiresolution segmentation, was used to create the objects (i.e. gullies) at
172 each level. The accuracy of gullies extraction was assessed using manually delineated
173 reference data collected from several field campaigns and resulted in an overall accuracy of
174 62%.

175 This paper aims to evaluate the combination of different simple morphometric indices to
176 characterize the morphological properties of gullies in a fuzzy logic framework, which is a
177 novelty in this field. The fuzzy logic framework is used in the Calhoun Critical Zone
178 Observatory (CCZO) where several gullies have been observed and mapped by others (e.g.
179 James et al., 2007) and where a very high resolution (i.e., 1 m) LiDAR DEM is now available.
180 The proposed procedure tries to automate the mapping of gullies and of the resulting gully
181 erosion patterns, which characterize the Calhoun area. The objectives of the paper are to

develop and assess an automated procedural chain of different algorithms to detect gullies based on their morphological characteristics retrieved from LiDAR DEM, and to develop and evaluate a method to measure main characteristics of gullies (i.e., depth and volume) : moreover, an overall assessment of the gully sediment yield at watershed scale is carried out with the aim to verify the consistency of gully erosion estimates provided by the presented methodology.

2. Study area and LiDAR Dataset

The CCZO is located in the USA's Southern Piedmont that extends from Virginia to Alabama, and is part of the CZO project, i.e. a project funded by National Science Foundation for the observation and the study of nine US natural "*critical zones*". The Calhoun experimental forest has a history that involves some of the most severe agricultural land and water degradation in the nation (Trimble, 1974). By the mid-20th century, nearly 18 cm of soil over more than 10 million ha were estimated to have been lost to erosion. Rivers carried enormous sediment loads and cultivation-based crops were no longer viable. A large numbers of farmers had abandoned the land when erosion and nutrient depletion became so severe that the land could no longer support cotton or tobacco crops. An estimated 200 km² of actively eroding gullies and severely eroded soils initially dissected the Sumter National Forest. By the late 20th century, the eroded and often abandoned Piedmont farmland had been extensively reforested, motivating many to adopt the perspective that the degraded land had been restored in a matter of decades by a process

known as “old-field succession”. Detailed information about this area is provided in the work of James et al. (2007).

The LiDAR data were collected as part of the CCZO project during a 2-day campaign (August 5, 2014 - August 6, 2014), with an Optech Gemini Airborne Laser Terrain Mapper (ALTM) (National Center for Airborne Laser Mapping, 2014). LiDAR point measurements were filtered into returns from vegetation and bare ground using the TerraSolid software (TerraScan Version 14.013) classification routines and algorithms obtaining a 1m DEM with horizontal datum NAD83, vertical datum NAVD88 and projection UTM Zone 17N. The absolute vertical accuracy has not been evaluated since no ground checkpoints were collected. For this reason a small vertical bias (<0.15 m) in the elevations of the final point cloud and DEM may exist with respect to NAVD88 (National Center for Airborne Laser Mapping, 2014). This accuracy usually degrades on steep terrain and under canopy. Additionally, a 1 m DSM (Digital Surface Model), which takes into account also the canopy, has been produced.

The LiDAR data cover an area consisting of a 13 km x 15 km rectangle (195 km²) located at 40 km SE of Spartanburg, South Carolina (Figure 1). Within this vast area, two smaller subareas have been identified to test and apply the proposed method. The first, called SUBAREA-A (Figure 2a), covers an area of approximately 1 km² where two gullies have been identified and mapped. The associated perimeters were defined during a field survey, carried out in June 2015, through a visual identification of the change in slope at the top of the gully walls (i.e. the point where the relatively flat gully margins starts to slope into the gully) and allowed for the calibration of the method aimed to the gully identification. The perimeter coordinates were acquired using a differential GPS total station (Topcon Hiper

Lite +) in RTK (real Time Kinematic) mode with a horizontal accuracy of about 25 cm. It is important to point out that, since the identification of gully edges is not always an easy task, especially when faced with cross sections with intricate shapes and diffuse limits (Casalí et al., 2015), a certain degree of uncertainty related to their identification and greater than the horizontal accuracy of the survey has to be taken into account.

The entire procedural chain here proposed has been applied to the second subarea (SUBAREA-B, with an area of 4.3 km² - Figure 2b), which corresponds to the Holcombe's Branch watershed, a tributary of Tyger river; this subarea was chosen since it includes several gullies, and represents a focal area of the CCZO project (Dialynas et al., 2016).

3. Methods

The methodology builds on the use of four different morphometric indices able to detect the presence of specific landforms, which can be interpreted as part of a gully. In particular two different sets of indices were used in this study: one index to detect the internal part of gully (gully bottom) and three indices to identify the gully boundary (gully edge) (Noto et al, 2015).

3.1 Morphometric indices

3.1.1 TPI for gully bottom

The first index, the *Topographic Position Index* (TPI) (Guisan et al. 1999), is also known as DFME (*Difference From Mean Elevation* - Gallant and Wilson, 2000) and has been used to detect gullies by Evans and Lindsay (2010). The TPI is defined as the difference between a cell elevation value z and the average elevation $\bar{z}_\alpha$ of the neighborhood around that cell

within the kernel of size α . Positive values mean the cell is higher than its surroundings while negative values mean it is lower. If z is significantly higher than $\bar{z}_\alpha$, then the cell is likely at or near the top of a hill or ridge. Significantly low values of z (and then of TPI) suggest the cell is at or near the bottom of a valley.

The normalized TPI was used here, obtained by dividing by the mean value of elevation within the used kernel ($nTPI$):

$$nTPI = \frac{z - \bar{z}_\alpha}{\bar{z}_\alpha} \quad (1)$$

The $nTPI$ was derived creating a specific function in GRASS GIS starting from the existing *r.neighbors* function; this function requires the definition of kernel size α among the other optional inputs.

3.1.2 Maximum curvature for gully edge

Surface curvature, which is the second spatial derivative of the terrain elevations, is one of the basic terrain parameters widely used in terrain analysis (Evans, 1979) and landform classification (Schmidt and Hewitt, 2004). The profile curvature (i.e., curvature of the surface in the steepest direction) and plan curvature (i.e., curvature of the contour) are the most frequently calculated topographic attribute (Gallant and Wilson, 2000).

Among the different methods used to derive curvature, Evans (1979) suggested two measures of minimum (i.e. concavity) and maximum curvature (i.e. convexity). Maximum curvature has been adopted as index of gully edge presence since the gully edges can be assimilated to convex slope breaks forming ridges (Tarolli et al., 2012).

The maximum curvature was used as index for gully detection here, and was derived from the DTM by applying methods developed by Wood (1996), which allows for a multiple-scale parameterization by generalizing the calculation for different kernel sizes. Following this approach a local surface is approximated using a bivariate quadratic function

$$z = c_1x^2 + c_2y^2 + c_3xy + c_4x + c_5y + c_6 \quad (2)$$

where z is the elevation, x and y are the planar coordinates and c_i ($i=1, \dots, 6$) are the quadric surface coefficients. This surface allows for the maximum curvature assessment using its coefficients:

$$c_{\max} = \alpha D \left[-c_1 - c_2 + \sqrt{(c_1 - c_2)^2 + c_3^2} \right] \quad (3)$$

where α is the size of the moving kernel and D is the DEM resolution. The maximum curvature was derived, within GRASS GIS, using *r.param.scale* function, which requires the definition of the size of the moving kernel α .

3.1.3 MinMax index for gully edge

The second index used to detect the edges of gullies is a focal map algebra function (i.e. filter) defined by Gallant and Wilson (2000) as ER (*Elevation Range*) and used by Johansen et al. (2012). This filter, here defined as MinMax operator, calculates the difference between the maximum and minimum values of elevation z present in a moving kernel of size α

$$\text{MinMax} = \max_{\alpha}(z) - \min_{\alpha}(z) \quad (4)$$

High values of this index may highlight the presence of strong discontinuities in the terrain surface (i.e. gully edge). The index was here normalized through the mean value of elevation $\bar{z}_\alpha$ of the kernel of size α .

$$nMinMax = \frac{\max_\alpha(z) - \min_\alpha(z)}{\bar{z}_\alpha} \quad (4)$$

Similarly to the $nTPI$, $nMinMax$ was derived creating a specific function in GRASS GIS starting from the existing *r.neighbors* function and also in this case kernel size α is the only input parameter.

3.1.4 Vosselman index for the detection of gully edges

This index is a filter derived by Vosselman (2000) and Vosselman and Maas (2001) to detect anomalies in the elevation of a LiDAR dataset usually originating from the pulses reflected e.g., by buildings, trees, cars, electricity wires, and other aboveground objects. The Vosselman filter is based on the observation that a large difference in elevation between two nearby points is unlikely to be attributed to a steep slope in the terrain. Likely, the higher point among the two is not a ground point. Clearly, for some difference in elevation, the probability that the higher point could be a ground point decreases if the distance between the two points decreases. Therefore, the author explicitly defined the “acceptable” difference in elevation between two points as a function of the distance between the points: $\Delta z_{max}(d)$.

For example, if the measurements are free from errors, the maximum acceptable level of differences is the function of threshold slope (β) and the distance d between points

$$\Delta z_{max}(d) = \beta d \quad (5)$$

In the usual case of noisy measurements, the author suggested to add a confidence interval to the criterion. If one would allow that 5 % of the terrain points with a standard deviation σ may be rejected, the filter function becomes

$$\Delta z_{max}(d) = \beta d + 1.65 \ 2\sigma \quad (6)$$

This filter, which was used here to detect the gully boundaries as anomalies of the terrain, provides, as outcome, a Boolean index (i.e. only 0 and 1 values are allowed, where 1 means presence of anomalies - boundaries). The central pixel of the moving kernel is classified as gully cell if there exists at least one pixel within the kernel with an elevation difference larger than the maximum acceptable level of differences for a given distance. A terrain slope threshold β is used to modify the filter function to match the overall slope in the study area and the confidence interval can be used to reject outliers during computation; besides the slope threshold, the filter requires also the kernel size as input.

3.2 Description of gully detection algorithm

The first step of the algorithm for the automatic detection of gullies is the derivation of the aforementioned indices ($nTPI$, c_{max} , $nMinMax$ and Vosselman index). All these indices require a careful definition of a support scale (i.e. the kernel size α). Moreover in the case of Vosselman index, the threshold slope has to be defined as well.

For the *nTPI* index, Evans and Lindsay (2010) suggest to choose the kernel size as a function of the typical width of the gullies to detect. In order to capture gullies at different scales, following the suggested approach, *nTPI* was derived at three different kernel sizes, equal to 10, 20 and 30 m respectively. The kernel sizes of the other indices, i.e. the maximum curvature c_{max} , *nMinMax* index and the Vosselman index, are instead defined through a calibration procedure detailed in section 4.

The four indices previously defined, which can be considered as markers of presence/absence of the gullies (bottom parts and boundaries), could be used in a typical Boolean framework aimed to the detection of gullies starting from a DEM (i.e. Martínez-Casasnovas, 2003; Evans and Lindsay 2010; Castillo et al., 2014). This approach 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.

However, two types of uncertainties affect this kind of procedure. First, the errors that characterize a LiDAR DEM (i.e. errors deriving from GPS position, inertial measuring unit orientation, and the laser rangefinder) are inevitably propagated to all DEM-derived primary topographic indices such as *nTPI*, curvature, slope, etc. Second, other uncertainties may arise from the definition of fixed thresholds, which characterizes the classical Boolean approach. When a threshold is fixed, two “similar” values of the analyzed variable can lead to two different outcomes, according to the Boolean approach (true/false or 0/1).

The use of a fuzzy logic approach allows to overcome these disadvantages, by deriving a map that provides a measure of the probability that each single pixel can be part of a gully instead of true/false characterization of the gully. The fuzzy set theory allows soft boundaries and vague landform classes to be explicitly represented, providing more information on landscape structure than discrete and often spatially disjointed Boolean landform classes (Schmidt and Hewitt, 2004; Arrell et al., 2007; Brzank et al., 2008).

The fuzzy logic is based on the *fuzzy inference*, which is a method that interprets the values in the input variable and, based on some set of rules, assigns values to the output variable. The fuzzy logic starts with the concept of a fuzzy set (Zadeh, 1965), which is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. A membership function (MF) 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.

The degree of membership of each pixel to the class of gully (bottom or boundary) was derived by applying specific membership functions to the indices $nTPI$ (for the gully bottom) and c_{max} and $nMinMax$ (for the gully boundaries). In this way, these continuous variables derived from the LiDAR DEM are transformed into a continuous variable ranging from 0 (no membership to the gully class) to 1 (full membership to the gully class). With regard to the membership function, the S-shape function was selected among the available mathematical equations normally used to depict MF:

$$f(x; a, b) = \begin{cases} 0 & x \leq a \\ 2 \left(\frac{x-a}{b-a} \right)^2 & a \leq x \leq \frac{a+b}{2} \\ 1 - 2 \left(\frac{x-b}{b-a} \right)^2 & \frac{a+b}{2} \leq x \leq b \\ 1 & x \geq b \end{cases} \quad (7)$$

where a and b are fixed parameters which locate the extremes of the sloped portion of the curve (Figure 3).

The application of S-shape MF to all the five indices layers (three $nTPI$ with different kernel sizes for the gully bottom and $nMinMax$ and c_{max} for gully boundaries) creates five different raster layers with value ranging from zero (no membership to the gully class) to one (full membership).

These raster layers are combined together using specific fuzzy rules. Several fuzzy operators (fuzzy intersection AND, fuzzy union OR, fuzzy algebraic sum, fuzzy algebraic product and fuzzy gamma operator) allow the flexible combination of different input raster layers derived by the application of MFs in a series of steps depicted by Bonham-Carter (1994). In this work two different fuzzy rules, namely fuzzy gamma operator and the fuzzy union OR, were used to combine fuzzy raster layers. The fuzzy gamma operator is derived by combining fuzzy algebraic sum together with fuzzy algebraic product, as follows:

$$\mu_{gamma} = \mu_{al,sum}^{\gamma} * \mu_{al,prod}^{1-\gamma} = [\prod_i^n \mu_i]^{\gamma} * [1 - \prod_i^n (1 - \mu_i)]^{1-\gamma} \quad (8)$$

where n is the number of fuzzy raster layers to be combined, μ_i is the fuzzy membership function for the i -th raster layer and γ is a parameter chosen between 0 and 1. Fuzzy gamma is a compromise between increasing tendencies of the fuzzy algebraic sum and the decreasing effect of the fuzzy algebraic product. With the γ factor, the decreasing or

increasing tendency can be controlled. When γ is equal to 1 (0) the combination corresponds to the fuzzy algebraic sum (fuzzy algebraic product). The fuzzy union OR operator is similar to the logical union (Boolean OR) and the output membership values are influenced by the maximum values of any of the input membership spatial layers, for any particular location.

Figure 4 describes the adopted algorithm, starting from the LIDAR DEM. After indices derivation, a fuzzy gamma operator was used to combine the three fuzzy *nTPI* (at scale 10, 20 and 30 m) and to combine the fuzzy layers deriving from *nMinMax* and $c_{\max}$. The output membership layer, deriving from the gamma operation between *nMinMax* and $c_{\max}$, was combined with the Vosselman filter (Boolean layer) through a classical Boolean intersection AND (i.e. equal to a local product operator). The fuzzy union OR was used to merge membership layers relative to the gully bottom and boundary in order to obtain a single layer representing the degree of membership to the class of gullies. This last operation (i.e., fuzzy union) has been carried out only on pixels representing gully bottom and on boundaries whose reciprocal distances were less than a fixed threshold, $D_{\max}$, here set equal to 10 m. This operation is required to avoid selection of high curvature areas not adjacent to valley bottoms or areas with very low *nTPI* surrounded by mild curvature.

The 'fuzzy' layer of the degree of membership to the class of gullies can be further processed in two alternative ways (Figure 5). The first consists of fixing a threshold of degree of membership (T_{dm}) and defining as gullies all the pixels whose value exceeds this threshold (*Option 1*), the second approach, *Option 2*, is based on techniques of image edge detection (Davis, 1975).

In order to detect edges in an image, several functions are available; these functions search places in the image where the intensity (i.e. pixel values) changes rapidly, using one of these two criteria: a) places where the magnitude of the first derivative of the intensity is greater than some threshold; b) places where the second derivative of the intensity has a zero crossing. Here the *Sobel* operator (Sobel and Feldman, 1968), which is based on the first criterion and is one of the most used filters to detect edges in images, was used.

This operator, which measures the spatial gradient in an image, consists of a pair of 3×3 convolution kernels with one kernel that is simply the other rotated by 90°. These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (named G_x and G_y). These can then be combined together to find the absolute magnitude G of the gradient at each point and the angle of orientation θ of that gradient as follows:

$$G = \sqrt{G_x^2 + G_y^2} \quad \theta = \arctg \frac{G_y}{G_x} \quad (9)$$

In order to identify the gully boundaries, the layer of the magnitude G has to be subject to a further thresholding process, but in this case it is possible to obtain an appropriate threshold value based on an intensity histogram of the image provided by the Sobel operator. The threshold value can be further adjusted by multiplying it with a correction factor C_f in order to increase or reduce the extension of extracted features.

The final outcome of both above-mentioned procedures (*Option 1* and *2*) is usually a Boolean layer raster (1 for gullies pixels and 0 for the background) where several 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., 1987; Haralick and Shapiro, 1992). These operators, which formally derive from the set theory, are able to process images, or raster layers, based on shapes, and apply a so-called *structuring element* to an input Boolean image, creating an output image of the same size. In general, the pixel value in the output image is derived by comparing the corresponding pixel value in the input image with its neighbors. By properly choosing the size and shape of the neighborhood, it is possible to build a morphological operation that is sensitive to specific shapes in the input image. 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, combines two sets using the vector subtraction of set elements, and removes pixels on object boundaries. The number of pixels added or removed from objects in an image depends on the size and shape of the structuring element used to process the image. In this case the following sequence of dilation, erosion and filling algorithms were implemented in MATLAB (Gonzales et al., 2009) in order to improve the shape of the extracted gullies (Figure 5):

1. dilate the Boolean raster layer using a vertical structuring element followed by a horizontal structuring element. The dilated raster layer closely approximates the

outline of the candidate gully quite precisely, even if some holes in the interior part of the candidate gully may still remain.

2. Fill holes in the interior of the candidate gully using a specific morphological function (Soille, 1999) which identifies holes in a Boolean raster layer as a set of background pixels that cannot be reached by filling in the background from the edge of the image, and subsequently fills them.
3. Clean the map using morphological cleaning function (Soille, 1999), because the candidate gully is successfully segmented, but some objects are still connected to the border of the image.
4. Smooth the gully object by eroding the raster layer twice with a specific structuring element in order to give a “natural” shape to the candidate gully.
5. Remove the isolated pixel cluster having an area less or equal to a threshold named A_{min} , here fixed equal to 40 m².
6. Extract the perimeter of the candidate gully using a further morphologic operator, which returns a Boolean raster layer that contains only the perimeter pixels of the gully in the input layer; this raster layer is finally converted in a vector layer.

3.3 Assessment of gully volumes

After the gully perimeter was delineated, the assessment of gully volume was carried out, using an approach similar to that employed by Daba et al. (2003) and Evans and Lindsay (2010) but using a more complex interpolation algorithm. Specifically, the procedure involves the following steps:

- a) the removal of elevation data within the gully boundary followed by the creation of a buffer around the gully perimeter;
- b) the transformation of pixel values within this buffer zone in points (x, y, z) (i.e. the transformation of a raster structure in a table containing the coordinates x, y, z of points belonging to the buffer zone);
- c) the use of such points to create a “*pre-gully*” top surface (only for the area covered by the gully) using an hydrological based interpolation method (ANUDEM, Hutchinson, 1988; 1989);
- d) the calculation of the gully volume as the difference between the “*pre-gully*” top surface DEM and the actual DEM;

The ANUDEM interpolation was carried out using TOPOTORASTER algorithm implemented in ArcGIS 10.1 using data points (point b), the central drainage line of the gully as streamline feature and excluding elevations value downstream the ending section of the gully.

4. Method calibration

The procedural chain proposed in this study involves making choices of many different parameters, which may influence the resulting outcome in terms of accuracy of the identification of gullies.

While some of these parameters were pre-set based on previous studies, values of other parameters have to be chosen in order to improve the identifiability of gullies and associated boundaries.

In particular, the following strategy, based on a mixture of heuristic and algorithmic approaches, has been adopted:

- 1) The kernel sizes (α) of the three morphometric indices, shown in Figure 4 ($nMinMax$, c_{max} and *Vosselman index*), were fixed *a priori* but, for each of these three indices, three different α were chosen starting from the outcomes of previous studies (e.g., Höfle et al., 2013; Tarolli et al., 2012; Johansen et al., 2012), and from an initial qualitative visual analysis. In particular, three different α for each of the three indices were set, i.e. α equal to 3, 5 and 7 m for $nMinMax$, α equal to 5, 7 and 9 m for c_{max} and, finally, α equal to 3, 5 and 7 m for the *Vosselman index* providing an overall number of combinations equal to 27. The *Vosselman index*, which provides as output a boolean layer, requires also the choice of the slope angle threshold (see section 3.1.4) here set equal to 30° in order to avoid the exclusion of large areas among those candidate as gullies.
- 2) The parameters a and b of the S-shape membership function (equation 7 and Figure 3) regarding the indices $nTPI$, $nMinMax$ and c_{max} were chosen equal to the 75th and 95th percentile of the relative variable.
- 3) The optimal values of the threshold relative to gully fuzzy membership map (*Option1*) or the threshold of the Sobel filter (*Option 2*) were robustly defined through an algorithmic procedure that uses a performance metric able to compare the results of the automatic procedure to the reference map of the gullies (i.e. field survey).

The metric used to compare reference gullies map with the spatial model outcome is derived by the error matrix (Cohen, 1960), which is a square matrix of size n equal to the number of the used classes (here only two classes are used: i.e. gully and no gully). The columns report the reference data (reference gully map) while the rows indicate the model predictions. The generic value x_{ij} ($i, j = 1, 2$) denotes the number of pixel of i -th class on the reference map reproduced by the model as j -th class. Pixels along the main diagonal represent correct reproduction by the model. The Kappa index, K , (Cohen, 1960) was calculated and used as performance metric:

$$K = \frac{N \sum_{i=1}^2 x_{ii} - \sum_{i=1}^2 x_{i+} \cdot x_{+i}}{N^2 - \sum_{i=1}^2 x_{i+} \cdot x_{+i}} \quad (10)$$

where x_{ii} (diagonal cells of the error matrix) represents cases where the predicted value agreed with the observed value, x_{i+} and x_{+i} are the marginal totals of row i and column i , respectively, and N is the total number of observations (total number of pixels in the area under study). K values provide an objective assessment of model performance. For instance, Fleiss (1981) characterizes K exceeding 0.75 as excellent, 0.40–0.75 as fair to good, and below 0.40 as poor.

The above-mentioned calibration strategy was applied to the gullies present within the SUBAREA-A. For a fixed combination of $n\text{MinMax}$, c_{max} and *Vosselman index*, the threshold value of the gullies membership map (*Option 1*) (or the threshold of the Sobel function – *Option 2*) were varied within an appropriate range; for each chosen value of the threshold, the procedural chain depicted in Figures 4 and 5 was executed to derive the gullies boundaries (i.e. layer of automatically extracted gullies). The automatically extracted boundaries were compared to those relative to the reference map (i.e. those measured

during the field survey) through the Kappa index. Therefore a K index was then associated to each threshold value at given combination of α of $nMinMax$, c_{max} and *Vosselman index*. As an example, Figure 6a shows the performance, in terms of K index, of the proposed method as a function of the threshold of the gullies membership map (*Option 1*) for fixed values of *Vosselman index*, C_{max} and $nMinMax$ kernel size α equal to 3m, 7m and 5m, respectively. The analysis shows that the Kappa performance index increases with the threshold value, it reaches its maximum (i.e. 0.876) for the threshold value equal to 45 and then decreases. A similar behavior can be observed for the *Option 2* case (Figure 6b) where a maximum value of K index (0.846) is achieved for the threshold value equal to 1.4. It is important to point out that in the *Option 1* case the performance metric values are always higher than 0.8 denoting the good choice of the combination of three morphometric indices, while for the *Option 2* a greater sensitivity to the threshold value is observed.

A total number of 3x3x3 combinations among $nMinMax$, c_{max} and *Vosselman index* (27 combinations) have been explored and, for each combination, the maximum value of the K index (i.e. peak of plots similar to those shown in Figure 6) was obtained for the two options. For example, the maximum values achieved with *Option 1* for each combination are shown in Figure 7. The figure reports three different subplots for each *Vosselman index* size (3, 5 and 7m) and, for each of these subplots, the maximum values of K index as function of C_{max} for three fixed values of α relative to $nMinMax$ (3m black bar, 5m white bar, and 7m gray bar). One can observe that, generally, the best performances in terms of K index are achieved, for fixed *Vosselman index* and c_{max} , for the intermediate value of $nMinMax$ α (i.e. 5m), even if this behavior is not observed for *Vosselman index* with a kernel size equal to 5m and for c_{max} α equal to 5 and 7m. In such cases the model performance decreases with

the increase of $n\text{MinMax } \alpha$. The best performance is achieved for the combination of Vosselman index with α equal to 5m, $c_{\max} \alpha$ equal to 7m and $n\text{MinMax } \alpha$ equal to 3m. Similar considerations can be provided by the analogous plot for *Option 2* which is not shown here for sake of brevity.

The use of the best performance combination (i.e. that characterized by the maximum K index) to SUBAREA-A has led to derivation of the gully boundaries shown in Figure 8, shown together with the boundaries surveyed in the field. One can observe that the boundaries of the two gullies are identified by the automatic procedure quite well. A first qualitative assessment of the fit of mapped gullies edges to the field survey is very encouraging suggesting that gully perimeters are well reproduced by the proposed approach. In some points of the study area, where the slope is milder, the proposed methodologies tend to recognize gully boundary with a lower reliability. In order to further confirm the good performances of the proposed method over the SUBAREA-A (already proved by the high value of K index), a quantitative comparison between reference perimeter and automatically identified perimeter was carried out for the two gullies shown in Figure 8 using a simple positional accuracy measure developed by Goodchild and Hunter (1997). The procedure compares a tested linear feature with a reference linear feature by computing the percentage of the length of the tested linear feature, which falls within a buffer of the reference source. This procedure showed that about 70% of the automatically extracted Box-DX gully perimeter (62% for the Box-SX gully) lies within 1 m of the “true” position; moreover, the 90th percentile of the buffer width (i.e. the buffer width which determines a coverage percentage of 90%) is equal to about 2m for Box-DX gully and 2.3 m for Box-SX gully. Considering that the pixel size of LiDAR DEM used in our procedure is

equal to 1m and considering also the uncertainty related to the manual identification of gully perimeter associated to GPS positional error, the accuracy of the gully perimeter identification can be assessed as more than satisfactory. With regard to the possible explanation for differences between reference and extracted gully edges, these could be due to the derivation of LiDAR DEM and its quality (shadowing of non-vertical laser beams, biased filtering of gully rims and data filtering used in the bare soil DEM preparation as highlighted in other previous studies) in addition to the uncertainties which characterize the proposed procedure.

5. Application to SUBAREA-B and gully volume assessment

Once the procedural chain had been calibrated using field surveys contained in SUBAREA-A, it was applied to the larger area, i.e., SUBAREA-B (Figure 2) in order to derive a map of gullies for the Holcombe's branch watershed and assess their characteristics.

The application of the procedural chain to SUBAREA-B, using the combination of parameter values that offered the best performance in SUBAREA-A, has led to the derivation of the gully map shown in Figure 9. All the gullies having extension smaller than a threshold area of 40 m² have been automatically removed from the final map. An analysis of the map yields the area and the boundary length (i.e. perimeter) of gullies together with other derived variables. The empirical distribution function (ecdf) of these derived characteristics are shown in Figure 10. A total number of 122 gullies were identified with an area (Figure 10a) ranging from a minimum of 78 m² to a maximum of about 5,500 m², whereas the perimeter ranges from 50 m to 1,180 m (Figure 10b). In order to characterize

also the shape of the extracted gullies, the compactness index (Figure 10c), which is given by the ratio between the perimeter p of the gully and the square root of its area A (multiplied by 4π) was estimated. This index ranges from a minimum of 1.23 (most compact gully) to a maximum of about 5 (very elongated gully).

The volume and the depth of the derived gullies were estimated following the procedure depicted in Sect. 3.3. Figure 11 shows, by way of example, the different steps followed to assess depth and volume of each gully identified by the proposed algorithm. The gully system used to depict the procedure, which is named Compartment 32 (James et al., 2007) is outside both the SUBAREAS (ULC 430380, 3831890 LRC 430650, 3831720 UTM zone 17 N). Specifically, starting from each gully boundary (Figure 11a), the elevation data relative to gully were removed from the original DEM creating an “hole” (Figure 11b); the elevation field of this “hole” was reconstructed through the interpolation method creating the “pre-gully” top surface (Figure 11c). The map algebra difference operator between the spatial layers containing the “pre-gully” top surface and the original DEM provides the spatial layers of gully depths (Figure 11d) which can be processed using spatial analysis techniques in order to obtain gully volume (function *r.volume* of GRASS GIS), and the average and maximum depths.

Figure 12 shows for the gully identified in the Box-DX of SUBAREA-A (which belongs to SUBAREA-B as well), three cross sections, namely A1-A2, B1-B2 and C1-C2. For these three cross sections Figures 12a, b and c show the original profiles (derived from the original DEM) together with the “pre-gully” profiles (derived with the interpolation procedure). The reconstructed profiles along the transects indicate interpolation procedure and gully filling routine seem to provide a morphologically consistent reconstruction of the elevation field.

The morphometric features of gullies identified within the Holcombe's Branch watershed have been analyzed through their ecdfs shown in Figures 10d, e and f. In particular Figure 10d shows the empirical distribution of volume whose values range from about 30 m³ to 11,180 m³; Figures 10e and f show the ecdf for average and maximum depth respectively with values ranging from 0.25 m (0.6 m) to 3.7 m (6.3 m). The main statistical characteristics of automatically extracted gullies are listed in Table 1 where measures of variability (standard deviation and coefficient of variation), which have been estimated as well, show the strongest spatial variability of volume and area (CV respectively equal to 1.65 and 1.06) and a greatest homogeneity (low CVs) for depth and compactness index.

It is worthwhile to emphasize that, the gully volume assessment can be affected by important errors caused by the different uncertainties, which characterize, as previously mentioned, the identification (both manual or automatic) of gully edges (Casalí et al., 2015).

6. Discussion

At the scale of the Holcombe branch watershed (SUBAREA-B, Figure 9), the mapping approach here developed provides a good definition of the spatial pattern of gullies development. The approach proposed surely requires further test to other gullied systems where good quality topographic data is available also allowing for the estimation of gullies volumes, which can be used as a sort of proxy of the average gully erosion rates at larger scale (i.e. watershed scale). The application of the method to SUBAREA-B provided the identification as gully candidates of some areas close to the main river channel, which were definitely not gullies but probably bank erosion landforms. Most of these areas were automatically removed because of their small area (less than A_s) while others were

manually removed at the end of automatic procedure. This problem could be solved by removing all pixel clusters adjacent to the main river channel (Castillo et al., 2014) or by introducing another threshold based on the contributing area.

One of the most important advantages of the proposed method consists in the removal of many uncertainties, which are related to the definition of fixed thresholds, which characterizes other approaches based on Boolean logic (e.g. Evans and Lindsay, 2010; Höfle et al., 2013; Castillo et al., 2014). Moreover, the normalization of two of the morphometric indices used in the proposed procedure allows for a scale-invariant derivation of gully characteristics that could be valid in other landscapes.

Some limitations of the approach must be emphasized: the most important parameters, which are calibrated using data of manual survey (SUBAREA-A), are those relative to the kernel size of the different morphometric indices. It is likely that these parameters are sensitive to the average size of the gully and, for this reason, they should be recalibrated in areas characterized by gully pattern different from those present in the CCZO study area. Moreover, the application of procedural chain might be unsuitable for landscape where the gully edges are not perfectly defined (low contrast in morphometric indices between gully edges and bottom).

The evaluation process carried out for SUBAREA-A, based on K index and the positional accuracy measure, could not be applied to SUBAREA-B because of the lack of data due to the great difficulties related to a complete survey over the entire watershed area. For this reason, only in this case, the performances of the procedure are evaluated based on the consistency of the gully sediment yield provided by the proposed method. Specifically, the

obtained values of gully sediment yield are compared with those found in literature in terms of erosion rate. According to the gully mapping of Figure 9 about 3% of the 4.3 km² of watershed area is covered by gullies, with an average gully depths equal to about 1.2 m. The total gullies volume, estimated through the proposed methodology, is equal to about 131,700 m³.

An appropriate value of the bulk density is required to quantify the mass of eroded material. Hansen and Law (2006), who analyzed the sediment measured from a discontinuous valley-side gully in the Sumter National Forest, South Carolina, observed that the bulk density of the sediment varies in a time window of about 10 years from a minimum value of 1.4 g/cm³ to a maximum value of 2.2 g/cm³. Richter et al. (2000), in work aimed to assess the effect of agriculture and forest regrowth in the nitrogen budget in old-field soils within Calhoun Experimental Forest, measured bulk density for 15 samples at different depths, obtaining an average value of about 1.4 g/cm³, with lower values close to the ground surface and relatively higher values at the depth of 30 cm.

If a range 1.4-2.2 g/cm³ is assumed for the bulk density of the sediment in the area, the weight of eroded volume from identified gullies is estimated to range between 184,000 and 290,000 t (or Mg). In order to obtain an average sediment delivery rate, one has to identify the time horizon characteristic of the gully erosion process in the CCZO study area. As mentioned in the Introduction, the Piedmont area of the southeastern US suffered a long period of erosion and gullying primarily due to intensive cotton cultivation. According to Trimble (1974) and Richter and Markewitz (2001), this period ranged from about 1820 to 1920 with a peak in erosion between 1860 and 1920. A decrease in the erosive processes

was observed after 1920, because of the agricultural decline, as well as a transition of cropland to pasture and forest, and a diffuse actuation of soil conservation practices.

Assuming also that these sediments have been eroded by the gullies activity in the last 190 years, even if the time intensity of this process has been recognized to be non-uniform, it is possible to estimate an average gully sediment delivery rate between 2.25 and 3.55 t ha⁻¹ year⁻¹ (or Mg ha⁻¹ year⁻¹) for the Holcombe branch watershed.

Bennett et al. (2000), Poesen et al. (2003) and De Santisteban et al. (2006) provided some useful statistics regarding soil loss from ephemeral gullies in different areas of the world. For the southeastern US, this value ranges between 1.9 and 17.0 t ha⁻¹ year⁻¹ (or Mg ha⁻¹ year⁻¹); it is important to point out that these estimated sediment delivery rates are derived at different scale (i.e. at gully scale or at watershed scale). This implies a different support (i.e. area) used to average in space the weight of the measured sediment loss, leading to relatively higher sediment delivery rate when the gully scale is considered, and lower when the rate refers to the watershed scale. The comparison between our assessment, which was carried out at a watershed scale (i.e. 4.3 km²), and values from the above-mentioned literature, highlights that our estimate (2.25 ÷ 3.55 t ha⁻¹ year⁻¹) is consistent with in the results of previous studies (1.9 ÷ 17 t ha⁻¹ year⁻¹).

Further analyses carried out by Galang et al. (2007) in a 7.5 km² area close the Sumter National Forest quantified the number and the morphological characteristics of gullies in this area. The values of soil volume eroded by gullies (ranging from 1.9 to 1734 m³) and of the corresponding depths (ranging from 1.0 to 5.3 m) are compatible with the ecdf of

volumes and depth shown in Figures 10d and 10f, respectively, further confirming the consistency of estimates provided by the present study.

7. Conclusions

In this work, an automatic method for gully mapping using topographic data at very high resolution (VHR) has been described and tested. The methodology is based on the joint use of three morphometric indices, used as detection variables, together with other morphometric variables, used only for selection purposes, within a well defined procedural chain which involves different spatial analysis techniques and image analysis algorithms. The main results of the applied methodology have demonstrated its capability to provide an efficient tool for gully detecting, mapping, and analyzing.

The fuzzy approach avoided the use of most of the fixed thresholds and of rigid rules needed to identify the gullies. The comparison between automatically extracted gullies and reference gullies (i.e. field survey) allowed the calibration the procedural chain and revealed a high correspondence, in terms of Kappa index, in polygon area values and in the spatial comparison derived by polygon overlay.

An interpolation-based algorithm was used to recreate a pre-gully surface which resulted in a reasonable first attempt, and could be improved in the future in terms of computational times and level of automation. The comparison between this pre-gully surface and the actual surface provided the morphological characteristics of the identified gullies (i.e. volume and depth), permitting an estimate of the total sediment volume eroded by gullies over the Holcombe branch watershed. The sediment loss rate, assessed based on assumptions on the value of bulk density and on the temporal interval of the erosive

process, was consistent with previous studies, even if the different uncertainties related to the gullies' edges identification may cause important errors in the determination of gullies' volumes, and in the consequent estimation of the eroded soil at a larger scale (i.e. at watershed scale).

With the increasing availability of LiDAR data, this automated technique has potential for applications across a range of environments. Future efforts will focus on implementing a robust version of this algorithm in a single software package (i.e. QGIS). A Python plug-in, able to wrap the different algorithms, could be developed in order to avoid the use of the three different software packages as done in the present work (QGIS, Matlab and ArcGIS).

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924

925 ***List of tables***

926 Table 1 – Statistics of automatically extracted gullies for SUBAREA-B: minimum, maximum,
927 mean value, standard deviation (STD) and coefficient of variation (CV) of the six gully
928 characteristics.

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930

	Min	Max	Mean	STD	CV
Area (m^2)	78	5152	861.8	911.6	1.06
Perimeter (m)	49	1181	240.8	214.7	0.89
Compactness index (-)	1.24	4.99	2.31	0.82	0.36
Volume (m^3)	27.2	11179.7	1078.9	1778.8	1.65
Average depth (m)	0.25	3.70	0.91	0.54	0.59
Maximum depth (m)	0.55	6.30	2.44	1.13	0.46

Table 1

List of figures

Figure 1 – LiDAR DEM of the CCZO and two SUBAREA limits used in this study. SUBAREA-A contains the surveyed gullies while SUBAREA-B is relative to Holcombe's Branch watershed (coordinate system UTM zone 17N).

Figure 2 – LiDAR DEM relative to: a) SUBAREA-A containing the two gullies surveyed (black line) and the computational boxes (blue line) used to evaluate model performance during the calibration; b) SUBAREA-B is the Holcombe branch watershed.

Figure 3 – Fuzzy S-shape membership function with the role of a and b parameters.

Figure 4 – Flow chart of proposed gully detection algorithm - part I aimed to the identification of layer of gully class membership values.

Figure 5 – Flow chart of proposed gully detection algorithm - part II aimed to the identification of gully boundary through image analysis.

Figure 6 – Kappa index as a function of threshold used for gully boundary delineation for fixed values of *Vosselman index*, $C_{\max}$ and *nMinMax* kernel size (respectively equal to 5m, 7m and 3m) using: a) *Option 1* and b) *Option 2*.

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Figure 8 – Gullies perimeter provided by field survey (black line) and from the proposed algorithm (purple line) for the two computational boxes (Box-SX and Box-DX) belonging to SUBAREA-A

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Figure 10 – Empirical cumulative distribution function (ecdf) of morphometric characteristics of gullies identified by the proposed algorithm over SUBAREA-B: a) area, b) perimeter, c) compactness index, d) volume, e) average depth and f) maximum depth.

Figure 11 – Gully volume assessment. a) Current DEM with gully boundary, b) current DEM after the removing of elevation relative to the gully, c) creation of the "pre-gully" top surface with the interpolation method, and d) difference between "pre-gully" top surface and current DEM (i.e. spatial distribution of gully depths).

Figure 12 – a) Gully of the computational BOX DX – SUBAREA-A together with three cross section profiles b), c) and d).

Figure 1

Legend

- Subarea A limits
- Computational boxes
- Gully perimeters (Field Survey)

a)

b)

Figure 2

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Figure 10

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