Mapping gullies using terrain-surface roughness

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Abstract

Gully erosion is a widespread and serious process of soil and land degradation. Mapping of gullies is important to quantify the amount of past soil losses, and to anticipate future erosion. Surface roughness obtained from remote sensing data often involves morphometric measures of terrain heterogeneity derived by unsupervised classification. We present a curvature-based method for computing surface roughness from digital terrain models (DTMs) derived from LiDAR (Light Detection And Ranging), and apply this metric for mapping gullies on Santa Cruz Island, USA. We estimate roughness as the log-transformed standard deviation of the total curvature in a fixed search window. We find that our method has potential for detecting gullies, if having high roughness contrasts to the surrounding landscape. We can obtain up to an overall accuracy of 0.89, and a Cohen's kappa of up 0.64 with this approach. Our algorithm has scope for wider applications and extensions to more coarse topographic data such as those from the SRTM (Shuttle Radar Topography Mission) to potentially recognize larger gullies or sharp-bounded channel and valley tracts at the regional scale.

Keywords: gullies, landforms, surface roughness, curvature, DTM, soil erosion.

1 Introduction

Gullying is a natural process and a consequence of running water eroding soils or unconsolidated cohesive materials. Gullying is an important signal of land degradation [1]. Mapping of gullies is essential to identify affected areas, quantify the size of the process, estimate the rates of change, and predict environmental consequences [2, 3]. Semi-automatic detection based on images has become a common method for mapping gullies [3, 4], and so has using mean elevation differences from light detection and ranging (LiDAR)-derived digital terrain models (DTM) [5]. Mapping of gullies based on other terrain derivatives such as total curvature or surface roughness remains relatively underexplored.

Terrain-surface roughness is a morphometric measure expressing how heterogeneous a land surface is [6, 7]. A DTM-derived roughness characterizes the local variance of surface gradients or curvatures, and enables distinguishing between smooth and rugged landforms or landforms elements. This property might be a useful indicator gully formation. Visual interpretation of DTMs shows that erosional landforms like gullies stand out from DTMs because of higher roughness than adjacent landforms. Previous studies [8-10] show that roughness can help to discern such landforms as well as the processes formed by them. However, how well this metric aids an automatic detection of gullies that are diagnostic of land degradation remains only partly understood.

We offer a method for calculating a roughness index based on the log-transformed standard deviation of total curvature extracted from LiDAR DTMs and its application in mapping gullies. We choose LiDAR data, because they facilitate high quality DTMs for areas covered by vegetation, where visual interpretation on optical images is often limited.

In the following we assess how well roughness is suited for detecting gullies in a study area prone to this type of erosion in California. Our objective is to introduce, test, and make available a new ArcGIS toolbox for evaluating terrain-surface roughness.

2 Previous works

The term roughness is defined and interpreted in several differing ways, depending on the field of study, the scale of analysis, and the aim of application [11]. Here we define the terrain roughness as a morphometric variable that expresses the local heterogeneity of a terrain surface.

A simple method introduced by Riley et al. [12] compute terrain roughness by estimating the variability of elevation, or slope in a local neighbourhood. Frankel and Dolan [13] suggested a method based on slope differences, by evaluating the standard deviation of local slope of every cell and its neighbours. An alternative using the standard deviation of residual topography was introduced by Haneberg et al. [14] and explained in detail by Cavalli and Marchi [15], and Cavalli et al. [16]. This method treats roughness as the standard deviation of the difference between the elevation and its locally smoothed derivatives within a moving square of 5-pixel side length. Similarly, Shepard et al. [17] proposed a set of algorithms based on the root mean square of elevation, relief and slope.

Other algorithms estimate surface roughness using point-cloud data. Glenn et al. [8] divided point cloud data into grid squares and identified the lowest elevation for each square. Using thin-plate spline interpolation of these minimum values, they estimated the height of every point above this surface, expressing roughness as the standard deviation of these height differences. Pollyea and Fairley [18] estimated surface roughness from a 3D point cloud with orthogonal distance regression, and fitted a local reference plane to uniformly spaced 3D grid cells. From this plane an orthogonal distance is estimated for every point, and the surface roughness of a given grid cell computed as the standard deviation of the orthogonal point-to-plane distances. McKean and Roering [19] advocated a more sophisticated use of slope statistics based on the direction cosines of normal vectors for each cell in the DTM.

Yet other methods used a two-dimensional discrete Fourier transform and a continuous wavelet transform [20]. These methods exploit the amplitude patterns of topographic features with respect to their frequency to estimate the roughness.

Grohmann et al. [21, 22] compared a number of existing roughness methods. The authors underlined the importance of moving window size for computing roughness statistics, together with the resolution of input data. They [21] also concluded that standard deviation of slope, standard deviation of profile curvature, and vector dispersion gave good results, depicting most terrain features. Also, [22] stated that simple methods like root mean square based algorithms, wavelet lifting scheme, and the direction cosines of eigenvalues performed well or even better than the more complex ones.

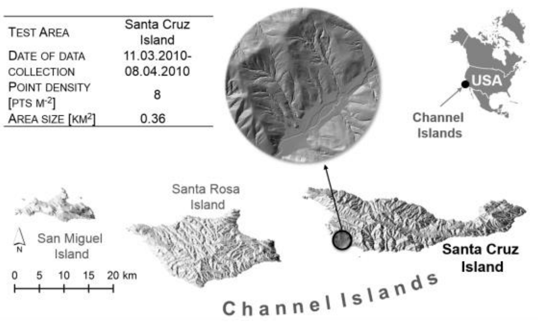
Based on these findings of previous studies, we use local (5 x 5 pixel) neighbourhood statistics of terrain curvature instead of slope or elevation for computing terrain roughness.

3 Study area and data

Previous studies [14], [19] argued that landforms linked to erosion have a roughness that differs from that of the surrounding landscape. To further test this hypothesis, we chose a number of gully sites to check whether our metric of surface roughness could reliably detect them. Our study area is in a grassland on Santa Cruz Island, California which is the largest island in the Channels Islands [Fig. 1]. Santa Cruz Island is affected by land degradation due to increase in the animal population in the 19^{th} century, this has affected vegetation denudation [2]. Although, further re-vegetation in this area has affected the slope stabilization, the gullying process on some parts still occur [23].

We used LiDAR data for evaluating surface roughness.

Figure 1: Test site and input data for testing the detectability of gullies from a surface roughness index.



These data are suitable for the purpose of our study because the laser-scanner signals are reflected below the vegetation canopy. This reflection allows filtering out those data points that originate from the vegetation, thus returning a terrain model that represents the bare earth surface [24].

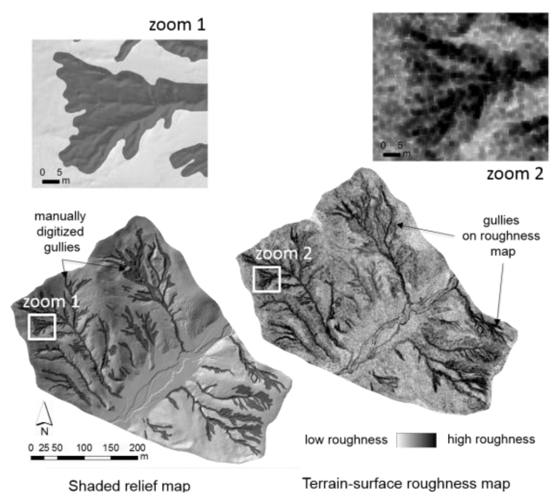
We obtained the data through the Open Topography [25] online portal. The data were acquired in 2010 with 8 pts/m² density [Fig. 1]. For generating DTMs from those data we used the classification for terrain and off-terrain points provided by Open Topography. We processed the data and generated the DTMs using the OPALS Software [26], using a moving-planes interpolation, and exporting it as a 1-m resolution raster.

4 Estimating terrain-surface roughness

We used a curvature map for estimating terrain-surface roughness following the method by Zevenbergen and Thorne [27]. They distinguished three types of curvatures, i.e. 1) profile curvature measured in the direction of the maximum slope; 2) planform curvature measured normal to the direction of the maximum slope; and 3) total curvature measured as the general curvature of the surface. Total curvature is thus the finite second derivative of the surface elevation, or the slope of the slope.

We introduce a roughness index based on the standard deviation of total curvature. The first step of our method involves estimating the total curvature with the *Curvature* tool available in ArcGIS, using the equations in [27]. We then computed the local standard deviation within a 5 x 5 pixel window, and interpret this as a metric of terrain roughness. The histogram of this metric has a high dynamic range, with most data clustering near zero, and only few data points having very large values. Hence we log-transformed the data to establish a numerically more convenient format [Fig. 2]. Surface roughness is high where the landscape is highly heterogeneous, and affected by gullying. Low roughness values coincide largely with smoother parts of the landscape

Figure 2: Detail of manually digitized gullies on shaded relief map and terrain-surface roughness.



such as most of the hillslope flanks and valley floors.

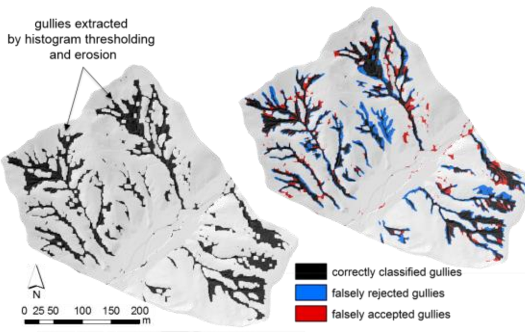
We implemented this algorithm as a toolbox for ESRI's ArcGIS 10.3 Desktop version.

5 Detecting gullies

How reliable is of our roughness index in mapping areas affected by gullying? We used a simple threshold in the roughness histogram to optimally capture the border of manually mapped gullies, which we used as reference data. We manually digitized all gullies from shaded relief map and a support images from Google Earth. Finding the threshold that results in the highest accuracy and the lowest commission and omission errors is a challenging task.

We selected the threshold by analysing the roughness histogram in a manual trial-and-error approach. We found that the highest discrimination between gullies and surrounding landforms was at a threshold equal of 1.47 [a.u.]. Comparing this threshold with reference data – that were generated by us by manually digitizing of the boundaries of gullies from shaded relief map – we observed that the outlines differed from each other. This is because we evaluated the standard deviation of total curvature in a 5 x 5 neighbourhood. To eliminate the influence of kernel size on our thresholding results we applied an erosion morphological filter [28]. We reclassified all pixels classified as gullies along their boundaries as not belonging to the gully class in a 2-pixel buffer [Fig. 3].

Figure 3: Detail of extracted areas affected by gullying and classification errors.



We verified the accuracy of our classification using standard statistical performance measures [29, 30]. We estimated the overall accuracy by dividing the total number of correctly classified pixels by the total number of pixels. The producer's, accuracy we evaluated as the number of pixels correctly classified as gullies divided by the total number of pixels assigned as gullies in the reference data. The user's accuracy we relates the number of pixels correctly classified as gullies to the total number of pixels classified as gullies. The Cohen's kappa is a means to rate the agreement of the classification.

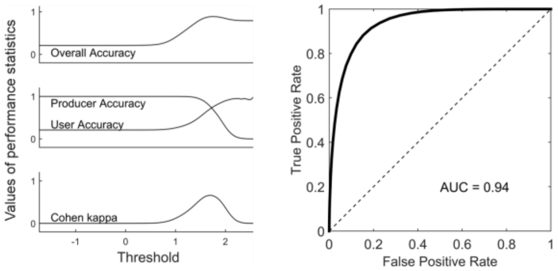
We find that a semi-automatic detection of gullies with our roughness algorithm, histogram thresholding and erosion filter achieve an overall accuracy of 0.89 with a Cohen's kappa of 0.64 [Tab. 1].

Table 1: Performance metrics of the classification.

Overall accuracy	0.89
Producer's accuracy	0.65
User's accuracy	0.77
Cohen's kappa	0.64

We also checked whether our classification obtained the highest possible accuracy from our terrain-surface roughness data, and calculated the receiver-operating characteristic (*ROC*) [31]. To this end, we selected one hundred different thresholds between the minimum to the maximum of our roughness data. We assessed the results by comparing the sensitivity (true positive rate) and fall-out measures (false positive rate) [Fig. 4].

Figure 4: Performance statistics for gully classification.



The area under the curve (*AUC=0.94*) of the *ROC* shows that our terrain-surface roughness index has a nominally high accuracy for detecting gullies. The overall, producer's and user's accuracy show that the highest accuracy that can be achieved from our index is 0.89, 0.73, and 0.73, respectively. The Cohen's kappa indicates that the highest possible interrate agreement of a classification using our roughness index is 0.66.

These findings suggest that our semi-automatic approach approximates the highest possible accuracy for detecting gullies. However, the trial-and-error approach is time consuming and potentially subjective. Therefore an automatic method like thresholding of a binary map for selecting an appropriate threshold is desirable. The automatic thresholding methods can work for example on analyzing the data histogram, clustering, and analyzing objects attributes.

6 Discussion

We propose a terrain-surface roughness index expressing the standard deviation differences of total curvature. We use curvature because it integrates local changes in both slope and aspect. Our results demonstrate a high accuracy of a semi-automatic mapping procedure for gullies using LiDAR-derived topographic data.

The highest accuracy of detecting gullies with our algorithm is likely to be tied to landscapes dominated by these landforms, while featuring few other distinctly different landforms. This is because our algorithm is blind to the type of detected object. Here expert knowledge and additional metrics, related to the shape, position and neighborhood, are necessary to distinguish between different landform types, and to ideally assign to each a characteristic roughness fingerprint. Nevertheless, we demonstrated that our roughness metric combined with thresholding and erosion filtering is useful for semi-automatically detecting gullies with high accuracy. Comparing the achieved overall, user's and producer's accuracy to previous studies [32], we find that our approach attains a better performance in detecting gullies.

We stress that the threshold values selected for this particular classification cannot be readily used as absolute values and transferred to other areas subject to gully erosion. Using a different point cloud density will influence DTM generation, and hence the roughness computation. Furthermore, the method selected for interpolation, and the selected spatial resolution of the topographic data will change the DTM input data [33]. Hence the threshold should be evaluated separately for every individual dataset. We also suspect that our algorithm may be useful for coarser Shuttle Radar Topography Mission (SRTM) data if the aim is to recognize larger-scale landforms such as sharp-edged river channels or valley segments at the regional scale.

7 Conclusion

Mapping of gullies is essential for detecting and quantifying soil degradation. Estimating surface roughness as a function of local differences in topographic curvature is a promising step for mapping erosional landforms and natural hazards from digital terrain models. We present a simple method for evaluating surface roughness and provide an implementation of our method as a toolbox for ArcGIS software.

Our tests show that the method has potential for detecting gullies, pending that they are characterized by sufficient contrasts in surface roughness compared to the surrounding terrain.

We anticipate that our roughness algorithm has scope for applications in other scientific disciplines concerned with objects having a surface roughness different from their surroundings. However, our algorithm also has some limitations. It is neither designed to—nor capable of—recognizing the type of detected landforms. Here an expert knowledge is necessary to recognize the analyzed landforms correctly. Future work may wish to focus on combining a roughness-based approach with data on landform shape, position, neighborhood, and automatic methods for differentiating types of landforms to work towards a more comprehensive classificatory approach.

References

[1] R.B.V. Shruthi, N. Kerle, V. Jetten, L. Abdellah, I. Machmach, "Quantifying temporal changes in gully erosion areas with object oriented analysis", *Catena*, vol. 128, pp. 262-277, 2015.

[2] R.L. Perroy, B. Bookhagen, G.P. Asner, O.A. Chadwick, "Comparison of gully erosion estimates using airborne and ground-based LiDAR on Santa Cruz Island, California", *Geomorphology*, vol. 118, pp. 288-300, 2010.

[3] R.B.V. Schruthi, N. Kerle, V. Jetten, Object-based gully feature extraction using high spatial resolution imagery, *Geomorphology*, vol. 134, pp. 260-268, 2011.

[4] S. d'Oleire-Oltmenns, I. Marzolff, D. Tiede, T. Blaschke, "Detection of Gully-Affected Areas by Applying Object-Based Image Analysis (OBIA) in the Region of Taroudamt, Marocco", *Remote Sensing*, vol. 6, pp. 8287-8309, 2014.

[5] M. Evans, J. Lindsay, "High resolution quantification of gully erosion in upland peatlands at the landscape scale", Earth Surface Processes and Landforms, vol. 35, pp. 876-886, 2010.

[6] M.W. Smith, "Roughness in the Earth Sciences", *Earth-Science Reviews*, vol. 136, pp. 202-225, 2014.

[7] V. Olaya, "Basic Land-surface Parameters," in *Geomorphometry: Concepts, Software, Applications*, vol. 33, T. Hengl and H.I. Reuter, Eds. Amsterdam, The Netherlands: Elsevier, 2009, ser. Developments in Soil Science, Ch. 6, pp. 141-169.

[8] N.F. Glenn, D.R. Streutker, D.J. Chadwick, G.D. Thackray, "Analysis of LiDAR-derived topographic information for characterizing and differentiating landslide morphology and activity", *Geomorphology*, vol. 73, pp. 131-148, 2006.

[9] A. Sagy, G.J. Axen, "Evolution of fault-surface roughness with slip", *Geology*, vol. 35, pp. 283-286, 2007.

[10] M.P. Bishop, L.A. James, J.F. Shroder Jr, S.J. Walsh, "Geospatial technologies and digital geomorphological mapping: Concepts, issues and research", *Geomorphology*, vol. 137, pp. 5-26, 2012.

[11] M. Milenković, N. Pfeifer, P. Glira, "Applying Terrestrial Laser Scanning for Soil Surface Roughness Assessment", *Remote Sensing*, vol. 7, pp. 2007-2045, 2015.

[12] S.J. Riley, S.D. De Gloria, R. Elliot, "A Terrain Ruggedness Index That Quantifies Topographic Heterogeneity", *Intermountain Journal of Sciences*, vol. 5, no. (1-4), pp. 23-27, 1999.

[13] K.L. Frankel, J.F. Dolan, "Characterizing arid region alluvial fan surface roughness with airborne laser swath mapping digital topographic data", *Journal of Geophysical Research*, vol. 112, pp. 1-14, 2007.

[14] W.C. Haneberg, A.L. Creighton, E.W. Medley, D.A., Jonas, "Use of LiDAR to assess slope hazards at the Lihir gold mine, Papua New Guinea", in: Proceeding,

International Conference on Landslide Risk Management, Vancouver, British Columbia, May-June 2005, Supplementary CD, 2005.

[15] M. Cavalli, L. Marchi, "Characterisation of the surface morphology of an alpine alluvial fan using airborne LiDAR", *Natural Hazards and Earth System Sciences*, vol. 8, 323-333, 2008.

[16] M. Cavalli, P. Tarolli, L. Marchi, G.D. Fontana, "The effectiveness of airborne LiDAR data in the recognition of channel-bed morphology", *Catena*, vol. 73, pp. 249-260, 2008.

[17] M.K. Shepard, B.A. Campbell, M.H. Bulmer, T.G. Farr, L.R. Gaddis, J.J. Plaut, "The roughness of natural terrain: a planetary and remote sensing perspective", *Journal of Geophysical Research*, vol. 106, pp. 777-795, 2001.

[18] R.M. Pollyea, J.P. Fairley, "Estimating surface roughness of terrestrial laser scan data using orthogonal distance regression", *Geology*, vol. 39, pp. 623-626, 2011.

[19] J. McKean, J. Roering, "Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry", *Geomorphology*, vol. 57, pp. 331-351, 2004.

[20] A.M. Booth, J.J. Roering, J.T. Perron, "Automated landslide mapping using spectral analysis and high-resolution topographic data: Puget Sound lowlands, Washington, and Portland Hills, Oregon", *Geomorphology*, vol. 109, pp. 132-147, 2009.

[21] C.H. Grohmann, M.J. Smith, C. Riccomini, "Multiscale Analysis of Topographic Surface Roughness in the Midland Valley, Scotland", *IEEE Trans. On Geosci. Remote Sens.*, vol. 49, no. 4, pp. 1200- 1213, 2011.

[22] M. Berti, A. Corsini, A. Daehne, "Comparative analysis of surface roughness algorithms for the identification of active landslides", *Geomorphology*, vol. 182, pp. 1-18, 2013.

[23] R.L. Perroy, Quantifying land degradation and vegetation recovery on southwestern Santa Cruz Island, California, Ph.D Thesis, UCSB, Santa Barbara, California, 2009.

[24] K. Korzeniowska, N. Pfeifer, G. Mandlburger, A. Lugmayr, „Experimental evaluation of ALS point cloud ground extraction tools over different terrain slope and land-cover types", *International Journal of Remote Sensing*, vol. 13, pp. 4673-4697, 2014.

[25] Open Topography. (2015) [Online]. Available: http://opentopo.sdsc.edu/, Accessed on: June 2015.

[26] N. Pfeifer, G. Mandlburger, J. Otepka, W. Karel, "OPALS – A framework for airborne Laser Scanning data analysis", *Computers, Environment and Urban Systems*, vol. 45, pp. 125-136, 2014.

[27] L.W. Zevenbergen, C.R. Thorne, "Quantitative Analysis of Land Surface Topography", *Earth Surface Processes and Landforms*, vol. 12, pp. 47-56, 1987.

[28] R.M. Haralick, S.R. Sternberg, X. Zhuang, "Image Analysis Using Mathematical Morphology", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 9, pp. 532-550, 1987.

[29] R. G. Congalton, "A review of assessing the accuracy of classification of remotely sensed data", *Remote Sensing of Environment*, vol. 37, pp. 35-46, 1991.

[30] J. Cohen, "A coefficient of agreement for nominal scales", *Educational and Psychological Measurement*, vol. 20, pp. 37-46, 1960.

[31] J.A. Swets, "Measuring the accuracy of Diagnostic Systems", *Science*, vol. 240, pp. 1285-1293, 1988.

[32] S. d'Oleire-Oltmanns, C. Eisank, L. Drăgut, T. Blaschke, "An Object-Based Workflow to Extract Landforms at Multiple Scales From Two Distinct Data Types", *IEEE Geosci. Remote Sens. Lett.*, vol. 10, pp. 947-951, 2013.

[33] S.M. Wise, "Effects of different DEM creation methods on the results from a hydrological model", *Comput. Geosci.*, vol. 33, pp- 1351-1365, 2007.