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Hydrology and Earth System Sciences Discussions

Interactive comment on "Channel network identification from high-resolution DTM: a statistical approach" *by* G. Sofia et al.

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First of all, we wish to thank Anonimous Referee #1 for his consideration and meticulous review of our manuscript. Anonimous Referee #1 raised very interesting issues and this helped us in improving and clarifying the work. We agree with the comments of the reviewer and we agree that all the underlined aspects needed a deeper and substantial clarification in order to make the paper more clear and thus the procedure applicable by other users.

The main issues identified have been:
1. Openness and curvature: explanation on why to combine them was needed;
2. Kernel size range: some indication on how to select the minimum and maximum

width were needed;
3. Filtering procedure: further explanation, as on why it was done on the extracted feature rather than on the input DTMs, were needed;
4. The cost-connection procedure: it substantially differs from the one referenced on the paper as Passalacqua et al. 2010a,b;
5. Quality evaluation: the chosen index referred to a unique value for the whole extraction, but it would have been interesting to see how it varies across the network.

Here our responses to the five issues previously reported:

Point 1.
The reviewer is right: in the mentioned works (Lashermes et al. 2007; Passalacqua et al. 2010a,b), curvature thresholding has been shown to be a powerful tool for feature extraction and this was the main reason for us to apply this parameters. We would like to underline that the extraction procedure we propose differs from the referenced one, where Laplacian curvature was derived after a smoothing of the input DTM: on our work, curvature (Evans', 1972), was directly derived from the original input DTM. Literature review suggests that small artifacts due to DTM interpolation, even when controlled and limited by appropriate methods, might amplify in first and second derivatives (Burrough and McDonnell, 1998; Gallant and Wilson, 2000). Being that there is not an unambiguous and objective criterion to assess ïňĄdelity of interpolated surfaces and/or revealed structures (McCullagh, 1988; Florinsky, 2005), we supposed that the reliability of network extraction would have gained from the integration of curvature with another terrain parameter not directly connected to surface derivatives. Openness measures convergences calculating the average of either zenith or nadir angles along azimuths (Yokoyama et al., 2002; Prima et al., 2006) and we assumed that this averaging procedure would have been less affected by artifact in the input data due to interpolation techniques. As suggested by Yokoyama et al. (2002), values of both positive and negative openness have been compiled.
For our work, DTMs were derived with two different interpolation procedures: the nat-

ural neighbour interpolator (Sibson, 1981) for the Cordon study site and an algorithm with a spline function in the ESRI TOPOGRID tool for the Miozza one (Tarolli and Tarboton, 2006; Tarolli and Dalla Fontana, 2009). We registered different behaviors of curvature skewness, for the two areas, while we registered constancy of dynamics for both positive and negative openness skewness in both applications (fig. 4A and B, p. 9358). Testing skewness behavior respect interpolation techniques, and identify relationship between curvature skewness behavior and input data was not a purpose of this work, but it was clear to us that openness and curvature behave differently. On the idea of finding a methodology that would have been valid among different datasets, independently from interpolation techniques used, we suggest that despite the fact that the information that both parameters carry might be redundant, the concavity/convexity detection might be more sound using both parameters.

Point 2.
The choice of the window size range refers to two main issues: a computational constrain that set the minimum size to apply, and an operational choice supported by previous works to set the maximum. The window size needs to be large enough for a reasonable number of data to be included in the evaluation but at the same time it need to avoid bias in surface computations. The choice of the minimum width relies on the fact that sampling windows are centered on the cell of interest, thus they consider (2n+1) x (2n+1) cells where n is an integer. The minimum window width is therefore 3x3 cells. To chose the maximum window width, we based our consideration on literature review. Pirotti and Tarolli (2010) demonstrated for the main study site of our work, that the window size for curvature calculations is related to the features to be detected: an over-sized window would dilute the distinct curvature feature by incorporating irrelevant elevation data, an under-sized window, on the other hand, would be less robust to noises. Tarolli et al. (2011) showed for the same study area a detailed comparison of feature extraction results based on different thresholding methodologies (including the QQ-Plot method adopted in this work) applied to a 0.5m DTM derivative evaluated for different kernel sizes. These authors computed maximum curvature

(Evans, 1972) considering a moving window size range from 3 to 33 cells (the same range applied on the present work). They demonstrated that that quality of extracted features, independently from the thresdholding methodology, tends to a progressive worsening when windows width is greater than 25 cells. They identified the best result as the one obtained through a moving window of 10.5 m (21 cells on the 0.5 DTM). For the present work, therefore, we applied the same kernel size range, and, using a 1m DTM, we did not consider moving windows greater than 33 cells (~33 m) because, as already proven, they more than likely would result in a too smoothed surface, less effective on the reproduction of suitable and detailed morphologies. We would like to underline that in our work, using the skewness procedure, we identified as optimal, a kernel size of 11m (11 cells for 1m grid size), very close to the optimum value (10.5 m) mentioned in the work by Tarolli et al. (2011). For Openness evaluation, it has been shown (Yokoyama et al., 2002; Prima et al., 2006) that the choice of the size of the investigated area (L in the original openness formulation, n as kernel width for the one proposed in this work) allows the representation of such parameters for fine to coarser scale features but there is no objective rule that can be used to determine such measure. Prima et al. (2006) calculated openness with operatively chosen width (L = 150 m and 5 km) to derive distinctive topographic patterns differed in scales. Consistently with the above referenced works for curvature evaluation, and to maintain homogeneity, we decided to apply the same kernel size range for Openness computation.

Point 3.
Before answering in detail to the reviewer about point 3, we would like to clarify that on our paper we address with the term ‘noise(s)’ the small scale variability representing actual concavity/convexity of the investigated surfaces but not necessarily a drainage network feature. Accordingly, we refers to ‘noise filtering’ as in the procedure to apply to discard these noises. Local concavities/convexities are typical in areas with complex morphology as the case of our study site and they have already been registered by Pirotti and Tarolli (2010), Tarolli et al. (2011), Passalacqua et al. (2010b). While on areas with smoothed morphology (as in the case of the Miozza test site) the small

scale variation captured is reduced to a pixel-scale width (therefore easily discarded), when morphological complexity increases, it is needed to identify a semi-objective way to guarantee noises removal. We suggest to filter the results of the extraction, instead of the input data, in order to have a map of the potential network as in detected surface convexities where to focus the efforts of filtering. Filtering the input data regularizing the map before computing attribute refers to a different approach for topographic attribute evaluation for feature extraction (Lashermes et al. 2007; Passalacqua et al. 2010a,b) and whose uncertainties have been already underlined (Passalacqua et al. 2010b). The method we proposed is based on a smoothing procedure to apply to the topographic attributes through the kernel size choice, rather than on a filtering of the original input dataset, therefore we decided to deal with noises on the extracted features. Considering the final Boolean map as an evidence of the localization of concavities, the user knows the location and the extent of the disruptions from the network. Analyzing Entropy (Gonzales et al. 2003) only for these doubtful features (as in elements with higher degree of discontinuity/disruption) the actual network delineation procedure is eased.

Point 4.
The reviewer is right. The two methods are substantially different, they just share the idea to connect the network skeleton according to cost functions, but they use two completely different approaches. According to the reviewer comment, on the revised paper, we will reference the cited works (Passalacqua et al., 2010a,b) avoiding comments about similarities between the procedures.

Point 5.
The total agreement probability as proposed, was used on a similar work for channel network extraction applied to the same investigated area by Pirotti and Tarolli (2010). Feature extraction quality measure based on a unique value for the whole extraction has been tested also by Tarolli et al. (2011). We used the unique value of Cohen's k in its original formulation as an overall quality measure, but considering the reviewer

suggestions, we decided to investigate the distribution of Cohen's k agreement among whole network (Figure 1), for the study site (A) and for the test site (B). To provide this information, we evaluate the index using a moving window of twice the size of the buffer considered for quality assessment (11x11). The results are influenced by the considered kernel size, but they are useful to provide a general overview. They confirm the previous conclusions, highlighting that the extraction procedure shows good agreement among the whole network, not only as an overall extraction but also locally. Some small areas with lower agreement refers to areas already underlined as challenging due to the presence of localized landslides (Passalacqua et al. 2010b, Tarolli et al. 2011), other refers also to constraints due to DTM cell resolution on identifying correctly network elements with a spacing smaller than the DTM grid cell.

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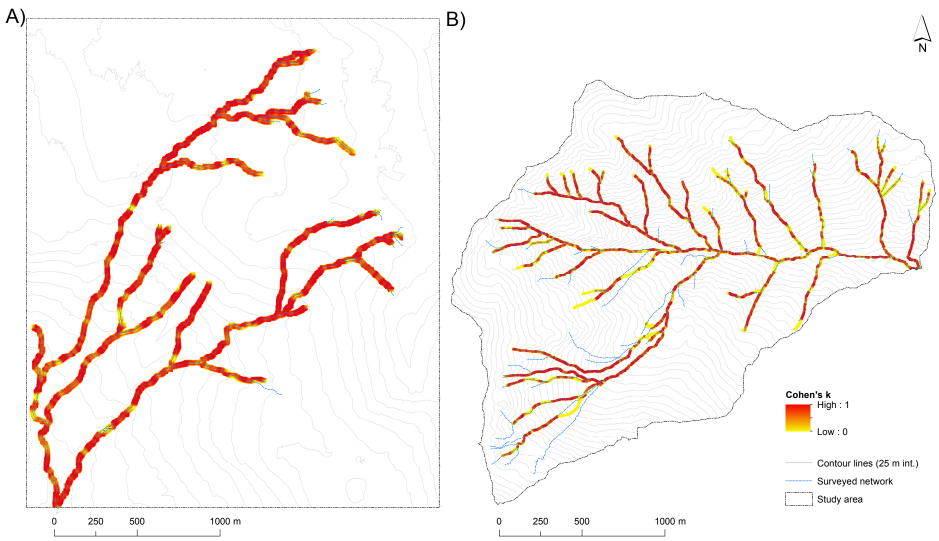

Fig. 1.