The subjects listed in the referee' comment, have been carefully addressed in the revised version of our paper. Hereby we are going to provide in detail our responses to the specific issues raised.

Point 1.
Done. The English has been revised.

Point 2.
According to the referee, on the revised paper we provided a flow chart of the procedure (Fig. 1). Hereby we are also providing a glossary with the used abbreviations. Considering that all the abbreviations are already explained in the text, we did not insert this glossary on the revised paper.

Glossary

A_{MDF}	Multiple flow direction upslope area
A_w	Weighted Upslope Area
n	Kernel size
n^*	Optimum kernel size
N_{TA}	Normalized topographic attribute
QQ-Plot	Quantile-Quantile Plot
$QQ\text{-}Plot_{thr}$	Threshold identified through the QQ-Plot
Sk	Skewness
Sk'	Skewness derivative
TA	Topographic Attribute (minimum curvature and openness)
TA^*	Topographic attribute evaluate for n*
W	Weight to apply to upslope area
Z_i	Standard score

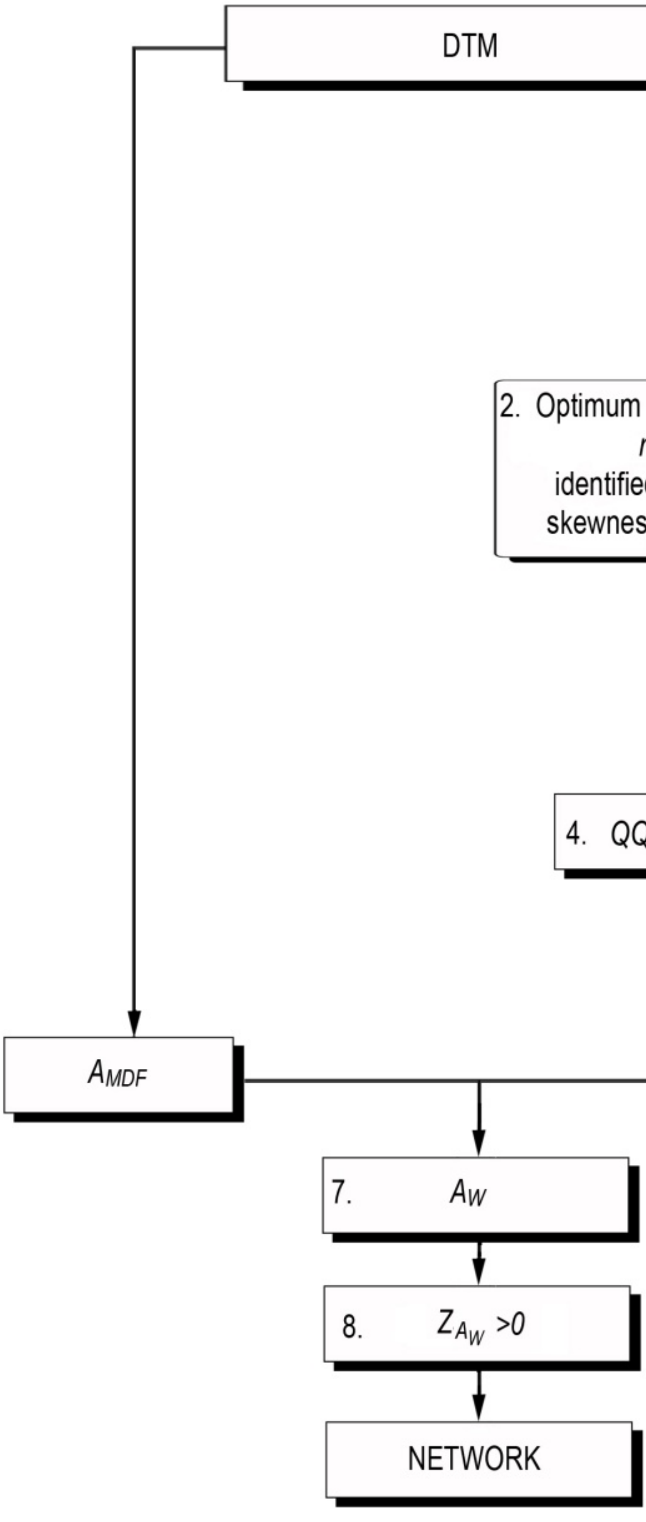

Fig. 1. Flow chart of the proposed methodology. 1) Evaluation of Topographic Attributes (*TA*) (Minimum Curvature C_{min}, Positive Openness ϕ_L, Negative Openness ψ_L, for different moving windows size; 2) evaluation of kernel size, through the analysis of skewness [for each topographic attribute, parametric fitting of a polynomial of degree *m* that fits the skewness data as a function of kernel size in a least square sense; derivative of the polynomials to evaluate inflection points; choice of optimum kernel size (n*)]; 3) topographic attributes evaluated for the optimum width; 4) QQ-Plot analysis and identification of thresholds; 5) normalization of each map according to its threshold; 6) evaluation of a weight matrix depending on the normalized topographic attributes; 7) weighting of the MDF upslope area according to the provided matrix ; 8) network identified as positive values of weighted area standard score. At this point, according to the presence/absence of noises, we provided an indication on how to perform a filtering approach and on how to connect the network.

Point. 3

On the paper introduction, we highlighted a summary of other works dealing with similar issues of extracting channel network, providing a scientific context. Considering the request of the referee, in the revised paper we highlighted some of the main differences between this work and the mentioned ones.

We will hereby briefly summarize some aspects.

In our work, we aimed to an unsupervised network extraction carried out without any a priori knowledge of the area or of the input dataset. The interest of this work relies on the research of a methodology whose parameters, as the optimal kernel size or the applied thresholds for network identification, can be objective and suitable for different applications, and they do not need a calibration on the data.

Considering to the scientific context mentioned by the referee, we would like to highlight three aspects concerning:

a) the type of topographic parameters used;
b) consideration of scale;
c) objective thresholds to compute the network.

a) We would like to underline that in our work, curvature has been evaluated according to Evans' (1972) formulation, using the same approach applied to mean and maximum curvature in Pirotti and Tarolli (2010) and Tarolli et al. (2011) respectively.
For the other works mentioned by the referee, instead, curvature has been evaluated with different approaches. Molly and Stepinski, (2007) applied the tangential curvature according to Mitasova and Hofierka (1993) formulation. Plan curvature and total curvature have been used by Thommeret et al. (2010) and Tarolli and Dalla Fontana (2009), respectively. The work of Tarboton and Ames (2001) relied instead on a proxy of curvature stemming from the Peuker and Douglas (1975) algorithm.

b) The curvature as expressed in works indicated by the reviewer required the use of fixed kernels of 2x2 (Tarboton and Ames, 2001) or 3x3 cells (Molloy and Stepinski, 2007; Thommeret et al., 2010). Some authors, instead, underlined how scale needs to be included when evaluating surfaces derivatives, in order to bring out the longer-range signal connected to meaningful processes signature and at the same time mask short-range noises (Lashermes et al. 2007; Passalacqua et al. 2010a,b; Pirotti and Tarolli, 2010; Tarolli et al. 2011). Considering this issue:
   i. Lashermes et al. (2007) and Passalacqua et al. (2010a,b) used a fixed operational scale to filter the input data;
   ii. Pirotti and Tarolli, (2010) identified the best window as the 15x15 cells one, but they underlined that this window might vary as a function of the size of the features to be detected;
   iii. Tarolli et al. (2011) underlined for landslides and bank erosion features, that a too small or too wide window size is not suitable for thresholding based on statistical descriptors and the best results were obtained considering a 21x21 cells window.

How to select objectively a scale for curvature evaluation, is still an open question, since the basic 3x3 moving windows has been proven not reliable for our study area (Pirotti and Tarolli, 2010, Tarolli et al. 2011). These works identified two different moving windows (corresponding to 15m and 10.5 m, respectively) as the best ones, relating them to the size of the investigated features. In these studies, furthermore, the optimum kernel size is identified a posteriori, through a comparison of all extractions carried out considering all possible kernel sizes (12 in both works) with the reference features, for a total of 36 (ii.) and 10,312 (iii.) -considering also the filtering procedure- comparisons.

We want, instead to identify this optimum size before proceeding with the extractions. The idea is to consider an approach relatively independent of the input dataset or from the size of the analyzed features. We would like to highlight that in our work the procedure identified an optimum kernel width of 15m for Openness (same window identified as optimal for Pirotti and Tarolli, 2010), and 11m for Minimum Curvature (same window identified as optimal in Tarolli et al. 2011).

c) Other works provided objective thresholds for network delineation, however:

   i. Thommeret et al., 2010 identified objective thresholds through a method that was data-dependent and data-driven because it relied on DTM noise parameters. This required the DTM quality to be evaluated first, with the limit that comes from the DTM noise determination;
   ii. Lashermes et al. 2007 and Passalacqua et al. 2010a,b identified as an objective threshold the QQ-Plot, that we also apply to normalize the topographic attribute maps. In these works, although, the scale used to filter the input data was operationally derived. Note also that in Passalacqua et al. (2010a,b) a small threshold in contributing area was arbitrarily chosen to improve the robustness of the method used to connect the network. The same authors stated that this threshold might vary according to the analyzed landscape. In the work of Lashermes et al. 2007, a few constraints were found necessary for network definition, which in some cases required manual intervention;
   iii. Tarolli and Dalla Fontana (2009) tested the effectiveness of statistical thresholds (one, two or three times the standard deviation of curvature) as a useful and objective methodology for recognizing hollows and related channel heads, but they did not make any consideration about the network;
   iv. Pirotti and Tarolli, (2010) applied the same objective threshold based on standard deviation as proposed in the Tarolli and Dalla Fontana (2009) to test its effectiveness on identifying the network. Nevertheless, their purpose was not to produce a fully-connected network. Furthermore, as we already reported in b), they underlined that the window related to the best results might vary as a function of the size of the features to be detected (implying an a priori assessment of the feature of interests);
   v. Tarolli et al. 2011 tested different thresholding methodology to identify geomorphic features (landslides and bank erosion, not channel networks), where the choice of the kernel size to apply was operational and its effectiveness was tested a-posteriori, through comparison of different maps to the reference features;

As we already underlined in 3b), in both iv. and v, the procedures required to apply all the thresholds (a total of 3 (Pirotti and Tarolli 2010) or 68 -one to five times four different statistic thresholds, with 0.25 steps- (Tarolli et al., 2011)) to all the produced maps. The definition of the best result was then done through a comparison of all extractions respect to the surveyed features. Both kernel sizes and thresholds, for these works, are therefore, calibrated on the result.

Clearly, the referenced studies required the selection of some parameters that controls the form of network extracted, and they required either a prior assessment of the input data or a calibration of the kernel size by interactively testing its effectiveness. The method we proposed, instead, is an unsupervised network extraction carried out without any a priori knowledge of the area or of the input dataset. Our procedure uses unique statistical indicators (Skewness, QQ-Plot, standard score…). The objectivity of these indicators is proven by applying the procedure to two areas with different morphology, whose DTMs' spatial interpolation methods differ (see also our response to point 5).

It is true that the filtering procedure for the most complex area (Cordon) required the user to identify doubtful extraction, but these were discarded according to an objective threshold as well (Entropy higher than the mean). The connection of the network, then, did not require manual interventions: considering that the noises were withdrawn, the network was simply defined starting it only where a convergence was denoted and connecting it to a pour point (identified as the point of maximum convergence of flows).

Point 4
We think that the statistic parts are useful in the text to provide a clear description of the methodology.

Point 5.
A clear comparison of classical channel network extraction and flow routing methodologies has already been deeply and successfully addressed by Passalacqua et al. (2010b) for the same study area of our work. Therefore, we did not provide this comparison. Several other studies, however, already pointed out that a robust delineation of stream networks cannot always be achieved by the popular steepest descent algorithm, and for some case studies should be based on direct detection of morphology in the DTM (e.g. Molloy and Stepinski, 2007; Lashermes et al., 2007; Tarolli and Dalla Fontana, 2009; Thommeret et al., 2010, Pirotti and Tarolli, 2010; Passalacqua et al. 2010a,b).
Concerning the use of both openness and curvature, the referee comment helped us to understand that some further explanations were needed. According to this observation, in the revised paper, we provided a brief highlighting of the reasons behind the choice. We hereby briefly explain the background context as well.
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). Since there is not an unambiguous and objective criterion to assess fidelity 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 natural neighbor interpolator (Sibson, 1981) for the Cordon study site (Pirotti and Tarolli, 2010) 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). In our work, a constancy of dynamics of skewness was found in both applications, analyzing positive and negative openness. Differently, we registered an heterogeneous behavior for curvature skewness (fig. 4A and B). Testing skewness performance respect interpolation techniques, and identify their relationship was not a purpose of this work, but it was clear to us that openness and curvature behave differently. Although the information that both parameters carry might be redundant, we suggest that the concavity/convexity detection can be more sound using both indexes. This choice has been done considering the idea of finding a methodology valid for different datasets, independently from interpolation techniques used.

Specific comments.

- *9329: 14-17 I think that this paragraph concerning the DTM filling procedures does not contribute to a better understanding of the problems the paper is dealing with. It should be removed.*

Done. Considering the referee comment, we removed paragraph 14-17 (9329). Furthermore, considering other suggestions, we provided a better clarification of the scientific context.

- *9330 The authors refer to a lot of other works that have provided interesting results in channel network extraction. However, the author should explain what is new in this work compared to the others.*

The referenced works dealt with subjective or fixed operational choices of different parameters, as in scale size to adopt to filter the elevation information and thresholds to compute the network. All require the selection of some parameter that controls the form of network extracted. See our answers to points 3 and 5 for a fuller discussion.

- *For easier reading, I suggest to merge section 3.1 and section 5. In section 3.1, the upslope areas calculation should be more clearly explain. Moreover, the choice of the MFD could be justified.*

According to the referee comment, in the revised paper we explained more clearly section 3.1.
It is true we did not describe in detail the multi-flow direction algorithm (MDF) we used, but this was done because the only difference between the referenced one (Quinn et al., 1991) and our application was to provide a matrix of the weight to apply to the evaluated upslope contributing area.
Hereby we will anyway summarize some points about the choice of the MDF algorithm.
Previous studies demonstrated that:

- computing total contributing area properly when dealing with divergent topography, involves suitable algorithms for handling multiple-flow directions (Tucker et al. 2001) as the one proposed e.g. by Quinn et al., 1991; Costa Cabral and Burges, 1994; Tarboton, 1997;
- multiple-flow methods appear to produce generally better results for hillslope, avoiding the concentration of flow in distinct, often artificially straight lines, as in the single-flow direction algorithms (e.g., Erskine et al., 2006).
- multiple-flow algorithms allow the recognition of parts of channels likely to be active also under conditions of low or moderate flow, and highlight minor channel features, which are involved in flow processes during flood;
- multiple-flow algorithms should be preferred for applications of upslope contributing area derived from higher-resolution DTMs (5- and 10-m grids) (Erskine et al., 2006);
- multiple-flow algorithms are more robust than single-flow (Seibert and McGlynn, 2007): using single-flow, a tiny elevation difference between two of the neighboring cells can have a large effect as one of the cells receives all the area. With multiple-flow, these differences have a less influential effect because both cells receive about the same portion of the accumulated area.

Considering these observations, we focused our attention to multiple-flow algorithms (Quinn et al., 1991; Costa Cabral and Burges, 1994; Tarboton, 1997). We decided not to consider algorithms such as digital elevation model networks (DEMON) (Costa-Cabral and Burges, 1994) because, even if they might have theoretical advantages, they are too complex and case specific to be implemented for most applications (Tarboton, 1997).
The choice of the Quinn et al. (1991) multiple-flow algorithm was based on two further considerations:

a) previous studies (Endreny and Wood, 2001) demonstrated that, compared to other flow algorithms, MDF (Quinn et al., 1991) was the least sensitive to terrain uncertainties;
b) the main disadvantage of Quinn's MDF (large degree of dispersion even for a convergent hillslope), was supplied in our work by incorporating a weight depending on local topographic conditions.

According to a), on the idea of providing a method that was not constrained by an a priori knowledge of the dataset, we supposed that the Quinn's MDF would have been more robust than others. We would like to underline also that, considering b), the use of the D-infinity (D∞) multiple flow direction model (Tarboton, 1997) was discarded, because its weighting according to our procedure would have stressed the flow convergences already limited by the algorithm theory itself.

- *Section 3.2. The surface approximation is quite known. I recommend the authors to shorten this section by referring to other works that deal with topographic indices computation as Evan, 1992 and Woods, 1996.*

We agree with the referee. In the revised manuscript, we referenced the surface approximation as suggested. We focused the description only on the generalization of minimum curvature to perform terrain analysis across a variety of spatial scales (Wood, 1996).

- *9337: 15 Justify this affirmation: "Differently, in the presence of noises and terrain roughness, such a histogram tend to be more or less skewed to one side". It does not seem so obvious in mountainous areas*

In hilly regions, imbalanced terrain elevation could affect the histogram distribution and make it skewed (Youan et al., 2008). It is true we did not analyze histograms of the input DTMs, but it is well known that DTM derivatives are influenced by input elevation data (e.g. Burrough and McDonnell, 1998; Gallant and Wilson, 2000). Curvature, for example, has a high sensitivity to high frequency changes of the surface (Wood and Fisher, 1993). Skewness of elevation data can control the shape of the distribution of derived topographic attributes, and in our study we registered different values of skewness according to the windows chosen to investigate convexities (Fig. 4A and B). The higher/lower skewing was due to the smoothing/enhancing effect derived by the different kernel sizes, and its smoothing/accentuation of noises and roughness.

- *9338: 10-14 Use X (random variable) instead of x in eq. 10. And latter un the text, keep X not t.*

According to the referee comment, we partly considered this suggestion. In the revised paper we used X (random variable) instead of x in eq. (10). We would like to underline that skewness, as it is referenced in this work, has been evaluated through the software Matlab®, and it has been described consequently. The Eq. (10) is consistent with the one referenced in the software (Matlab, 2010b). The variable t refers to the expression included in the brackets (X-μ) not to the random variable itself.

- *9339: 5-end of the section I wonder if these paragraphs should not be with the results.*

We think that sections 5 to 7 included, refer to methodology. Results focus instead, on the quality of the extracted network.

- *9340:4-10 Refer to other works that used the upslope area weighting procedure.*

Done. According to the referee comment, we added some references for the area weighting procedure as Liu et al., 2007 and Tarboton, 2003.

- *9340: 19-end of the section Justify the use of QQplots instead of a distribution comparison test as the chi2 test, for instance.*

We applied the QQ-Plot instead of other tests because this operator has already been successfully proven to be a strong indicator for concavity/convexity discrimination when applied to network extraction (Passalacqua et al. 2010a,b; Lashermes et al., 2007) and to geomorphic feature extraction

(Tarolli et al. 2011). We did not want to test the actual normality of the dataset, but we wanted to identify a threshold defined as the point of divergence of the dataset from normality.

- *9341 Concerning the z-score: I'm not sure it is the appropriate name (standard score) while population parameters are estimated. If it means normalized variable, or stundentized variable, just refer to it and synthesize this section in one sentence.*

In statistic a standard score (z) is defined as a dimensionless quantity derived by subtracting the sample mean from an individual score and then dividing the difference by the sample standard deviation. The "studentized" equivalent require the denominator of the formula to be normalized according to the square root of the dataset size. Z-score, as it is referenced in this work has been evaluated through the software Matlab® and it has been named consequently. The software with its Standardized z-scores procedure "returns a centered, scaled version of the input data, the same size as the input" (Matlab, 2010b). The formula applied is the one in Eq. (17). Considering the reviewer comment, to avoid misunderstanding, in the revised paper we referenced this value as 'standard score'.

- *About the section 7: Is it possible to quantify the noise before the filtering step?*

Filtering the input data regularizing the map before computing a topographic attribute refers to a different approach for topographic attribute evaluation for feature extraction (Lashermes et al. 2007; Passalacqua et al. 2010a,b). 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. 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 necessary to identify a semi-objective way to guarantee noise 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. 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 a higher degree of discontinuity/disruption) the actual network delineation procedure is eased.

- *Section 9. It could be interesting to summarize the number of parameters and thresholds used to obtain the channel network.*

To ease the comprehension of the work, in the revised paper we provided a general schematization of the procedure that summarizes the steps required to obtain the channel network.

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