Answers to Anonymous Referee #1

The manuscript introduces a new and apparently user-friendly software, called r.slopeunits, for the automatic subdivision of the terrain into terrain units (i.e. slopeunits; SU). From a geomorphological perspective, the parameters "a" (minimum size of slope-units) and "c" (circular variance of slope aspect) represent the crucial parameters to control the size and orientation (i.e. aspect) of the SU. An optimal subdivision of the terrain into SU (measured with the introduced segmentation metric F(a,c)) is characterized by a high internal homogeneity (i.e. low local aspect variance within a SU) and a high external heterogeneity (i.e. high variability between SU) of SU. The authors also propose an approach to identify the "best" combination of "a" and "c" to generate SU for statistical landslide susceptibility modelling. This procedure is based on the previously mentioned SU segmentation metric and the fitting performance of the generated landslide susceptibility models (measured with the metric AUROC). The optimal terrain partitioning for landslide susceptibility modelling is then based on a combination of high segmentation performance of SU (F(a,c)) and a high fitting performance (i.e. high AUROC) and measured via the introduced function S(a,c). Software and optimization approach were tested in Central Italy, where landslide susceptibility was modelled using logistic regression and a large set of potential predictors. The quality of the present discussion paper is – for its most part - high and contains very useful graphs. From my perspective, the application of r.slopeunits appears to be very useful for a variety of purposes, but especially for empirically-based landslide modelling (e.g. landslide susceptibility modelling, probabilistic hazard modelling, etc.). The presented model is able to account for multiple important details (e.g. minimum area, removing odd-shaped units) and seems to be sophisticated from a technical perspective. I think that the usability/limitations of SU-based approaches, as well as the presented optimization-approach, should be discussed more thoroughly (see comments below).
I recommend a moderate revision.

We thank the Referee for ranking our manuscript high-quality, and for judging our approach useful and sophisticated. Below, we will try to address general and specific comments and to describe the modifications we have made to the manuscript.

I believe that the paper would improve by addressing the following issues:

(i) Adding some discussion on advantages and limitations of the presented model and optimization-approach. E.g. As a potential user of the software, I am very interested on why I should favour SU (e.g. over more easily applicable grid-based approaches) for the purpose of landslide susceptibility modelling. What are potential advantages and disadvantages of the presented software and SU-based landslide susceptibility models in general? (ii) Shifting some text parts to other sections respectively slightly restructuring the paper (see comments below) (iii) Reducing some redundancies within the text (see comments below) (iv) Modifying some figures (see comments below)

Specific comments:

1. From my experience, the boundaries of SU do not directly correspond to the units used by spatial planners (i.e. spatial planning-units are not equal to geomorphic units which is somehow addressed also in p. 11 line 21f)). For me, grid-based landslide susceptibility models appear more flexible in this respect as they can be (with some limitations) regularly and easily adapted to such boundaries (e.g. aggregating pixel values etc.). Discussion of such issues would shed more light on the usability of the presented software.

In the original version of the manuscript, in the "Introduction", we stated that "*Compared to other terrain subdivisions, including grid-cells or unique-condition units, SU are related to the hydrological and geomorphological conditions and processes that shape natural landscapes. For this reason, SU are well suited for hydrological and geomorphological studies, and for landslide susceptibility modelling and zonation*". There are conceptual, technical and practical reasons to favor slope-units as "best" (i.e., "optimal") mapping units for landslide susceptibility assessment and zonation. As a matter of fact, landslide phenomena are naturally bounded to occur within hillslopes, which makes slope-units the natural choice as a mapping unit of reference for landslide susceptibility. Indeed, there is a causal relationship between hydrologically consistent slopes and (most of the) landslides. The same cannot be said for other types of mapping units including e.g., grid cells or unique conditions units [A detailed description of the advantages and limitations of most of the terrain mapping units commonly used for landslide susceptibility assessment can be found in Guzzetti F. (2006) Ph.D. Thesis, Landslide Hazard and Risk Assessment. Mathematisch-Naturwissenschaftlichen Fakultät der Rheinischen Friedrich-Wilhelms-Universität University of Bonn, Bonn, Germany]. A suitable definition of such "slopes" and their delineation (i.e., the identification of "slope units") is the aim of our work. From the technical point of view, the use of a regular grid for landslide susceptibility zonation requires the use of parameters which are not related to the "real world" including e.g., the resolution of the grid, or the distance from landslide features (pixels or polygons) to be considered relevant for landslide zonation. These problems are overcome by using geomorphologically meaningful mapping units. From the practical point of view, we maintain that the fact that planners are not currently using slope-units is also (or even largely) due to absence of susceptibility maps prepared on a slope-units basis. We also maintain that a grid-based susceptibility zonation, and the associated map, is not more practical than a slope-unit based zonation, as it is virtually impossible to recognize grid boundaries in the field, whereas slope units are "*easily recognizable in the field*". On the other hand, it is equally possible to overlay the slope-units and administrative planning-units as it is to aggregate pixels within the same planning-units.

2. SU are related to hydrological and geomorphological conditions and therefore well suited for landslide susceptibility modelling (cf. p.1, line 20f). The delineation of SU does not consider any quantity other than terrain aspect. Thus, I assume that a single SU, which is represented by similar slope aspects, may as well exhibit a high intervariability of other landslide-influencing topographical properties (e.g. high slope angles in the upper part and low slope angels in the lower part). Thus, there might be as well a high intervariability of landslide susceptibility within a single SU, because the inclination of a slope is directly related to shear stresses. This might be one drawback of SU within the context of statistical landslide susceptibility modelling and should be discussed within the paper. Furthermore, I wonder if a consideration of the variability of slope angles (or a combination of slope angels and terrain aspect) would be possible or reasonable when dividing the terrain into homogeneous areas for the purpose of landslide susceptibility modelling?

It is true that variability of aspect direction is not the only possible choice for driving a terrain partition into distinct units. In the first place, it should be noted that our algorithm first operates a *hydrological* subdivision of the terrain, and variability is determined within the obtained half-basins at each iteration. An aspect-based measurements of variability determines the degree to which half-basins are facing different *directions*, while a slope-based variability would determine – in many places and morphological settings – a completely different situation. The example presented by the Referee is a good one. For our purposes, slopes containing two or more modes of the slope distribution (e.g., along the downslope direction) pertain to the same slope-unit, since a landslide can actually travel from one region of the slope-unit to another even if, and sometimes even because, the two regions differ in slope angle. However, landslides cannot travel horizontally from one region to another, if they have substantially different average aspect direction. We have coded in our algorithm a *desired* feature, by considering aspect direction variability instead of slope variability. A second reason for *not* considering slope variability is that slope is known to be the main explanatory variable in many landslide susceptibility models. We want our slope-units delineation algorithm not to be directly dependent on such variable, in order not to introduce a bias on the subsequent susceptibility zonation. From a technical point of view, any raster map could be used as a variability measure (and as a measure of segmentation quality) and a more general (unpublished) version of our code actually contains such feature, useful to use the algorithm for different purposes other than landslide-related studies.

3. If I am right, SU affected by only one landslide are treated equally as those units affected by e.g. 10 landslides (= landslide-presence unit). In other words, SU-based approaches do not differentiate between slope units slightly (e.g. 3% of the area) or highly affected (e.g. 80% of the area) by landsliding. From my perspective, such tendencies might also affect the final susceptibility modelling results. This argument further highlights that a detailed discussion of advantages and disadvantages of SU (in the context of landslide susceptibility modelling) may be highly beneficial for potential users of r.slopeunits.

The way we use landslide presence is stated in Section 5, where we write "*Adopting a consolidated approach in our study area, SU with 2% or more of their area occupied by landslides are considered unstable (having landslides), and SU with less than 2% of the area occupied by landslides are considered stable (free of landslides). The 2% threshold value depends on the accuracy of a typical landslide inventory map. We acknowledge that the selection of the 2% threshold may influence the selection of the appropriate SU subdivision, and may affect the results of the LS zonation. Examination of different thresholds is not investigated in the present work, because is not an input parameter of the r.slopeunits software, and does not change the logic of the approach or the rationale behind our optimization procedure*". The threshold value used in this work was established previously in the same study area, and here we assume it is a good estimate. We acknowledge that the threshold may be different in other study areas, or for different susceptibility models, or other different settings but establishing this is not within the scope of our paper. Different thresholds or even a different approach can be selected by the user to subdivide stable/unstable slope units. In addition, we comment on the usefulness of slope-units on this point. A slope-units is considered as stable or unstable in its entirety, on the basis of a single parameter *i.e.,* the mentioned threshold. This is consistent with the fact that each slope-unit can be considered as the result of a given set of geomorphological processes and hence homogeneous for what concerns landslide predisposing factors. It follows that it does not really matter *where* and/or *how many* landslides have occurred in a unit, but only if the unit is large enough (larger than a meaningful threshold). This is particularly true when landslide inventories are incomplete (a common case in geomorphology). The abundance of recognized landslides in a mapping unit does not mean that the unit has a higher instability than a nearby unit where the number of observed landslides is lower. The concept is particularly relevant if we consider a landslide inventory as a "sample" of the real landslide history of a slope unit. In this sense, just one single landslide should be enough to define a slope unit as unstable.

4. The authors mention that "a detailed terrain partitioning, with many small SU, is required to capture the complex morphology of badlands, or to model the susceptibility to small and very small landslides (i.e. soil slips)" (p. 15, line 2f). Please provide clarification if or how the proposed optimization approach accounts for terrain complexity (i.e. are there other parameters than terrain aspect?). For instance, does the optimization approach favour small SU in the case of complex terrain morphology or very small landslides or should the users decide by themselves on those parameters (which would be in contradiction to the proposed optimization approach)? Is the portion of SU considered as presences (= affected by landsliding) higher in the case the respective units are larger? If yes, does such a change in the ratio between landslide-presences to absence systematically change subsequent modelling results? E.g. Figure 10 suggests that the total areal extent of susceptible areas increases with an increasing SU-size. Could this also influence the apparent fitting performance of the model? Please discuss.

The r.slopeunits algorithm is designed to take into account the different degree of complexity in different regions within the same study area. From a technical point of view, this feature is provided by the iterative procedure. This is explained in detail in Section 3.1, "*Slope-unit delineation algorithm*", and illustrated in Figure 2. The idea behind the algorithm is stated in Section 3, where we write "*The [second] strategy defines an initial small number of very large areas, and reduces progressively their size until a satisfactory result is obtained*". Then, Section 3.1 explains in detail that the progressive reduction of the size of the slope units is stopped at different levels of granularity in different regions of a study area, depending on whether the constraints posed by the *a* and *c* parameters are fulfilled. The value of *c*, in particular, causes the iterations to stop earlier in the regions where variability is lower, resulting in larger slope units, whereas in more detailed (and more geomorphologically complex) regions the iteration is continued, resulting in smaller slope units. The desired "*adaptive*" feature of the algorithm is thus achieved.

As far as the optimization procedure is concerned, which is not contained in the r.slopeunits software itself, but it is a further action described in this work, it does not explicitly take into account the degree of complexity captured by the slope-unit delineation, but it considers (i) the aspect segmentation quality and (ii) the susceptibility model performance. In other words, (i) capturing the complexity of the terrain is a task accomplished by r.slopeunits; (ii) the optimization procedure is designed in such a way that a combined aspect segmentation quality and susceptibility model performance is maximized simultaneously. In the specific case of landslide susceptibility modelling, we can only expect that the LRM performs better when slope-units are better suited (because of their shapes and sizes) to a particular landslide inventory, since the model uses the explanatory variables more efficiently.

5. The findings demonstrate that the number of significant variables generally increased with a decreasing size of slope-units. Predictors related to local terrain settings (e.g. slope angle) were frequently neglected by the models while especially predictors related to lithology controlled the final landslide susceptibility modelling results. From the text, I deduce that the dominance of lithological parameters is related to an increasing SU-size. The authors finally infer that a logistic regression model generated for an area represented by very large SU "can be replaced by a simple heuristic analysis of the lithological map" even though high AUROC values might be achieved (p .13, line 20f). I think that this observation further indicates that a purely quantitative optimization of a SU-partitioning might (in some cases) not be sufficient to produce high qualitative SU-based landslide susceptibility maps. Please discuss.

The understanding of the Referee about the dependence of the significance of explanatory variables as a function of the slope-unit size is correct. As a matter of fact, we investigated wide ranges for the *a* and *c* parameters, a few combinations of them resulting in unrealistically large/small slope units. The discussion quoted by the Referee is meant to illustrate the inadequacy of such slope-unit delineations, and the limitations posed in those regions of the (*a*, *c*) parameters space, by an uncritical use of AUC_{ROC}. In the region of very large slope-units AUC_{ROC} gives a result which is not acceptable: large values of the metric correspond to a poor statistical significance of the explanatory variables and to results which is not of any practical use, since susceptibility maps prepared with large units have no meaning. The fact that slope angle is not significant indicates that slope units are probably too large, and each of them containing any value of the terrain slope angle, so that the LRM cannot discriminate between values of slope causing or not causing landslides. The behavior of the AUC_{ROC} is known in the literature, and it is simply due to the metric being a synthetic index that summarizes in one score the results pertaining to an arbitrarily large study area, with no further dependence on different geographical locations. To our knowledge, a metric that can take into account the complexity of the problems like the one we discuss in our paper does not exist, and we can only rely on existing tools. In our discussion we also clarify that we proposed one possible metric. Users can select other metrics, and replace AUC_{ROC} with a different and possibly more suitable metric, according to a specific problem and their personal judgment and understanding of the problem at hand.

We stress that the merit of our optimization procedure is that we provide a *quantitative* way of rejecting situations like the one described above, rather than relying on common sense (*i.e.*, using arguments like “slope units are too large or too small”), pre-existing results or maps (*i.e.*, a different method produced a susceptibility map from which our result cannot be too different), or other forms of personal or heuristic judgement. We proposed an overall performance metric, S(a,c) = F(a,c)R(a,c). The function is the sole metric we use to determine the optimal values of the parameters, and the maximum of S(a,c) in our test case is indeed far from the limiting-case situations of slope-unit with unrealistic sizes. In conclusion, we proposed a working solution that can be criticized or improved, but it certainly is a rigorous solution.

6. The proposed combination of the aspect segmentation metric and the AUROC metric appears logical from a purely quantitative perspective. The subsequent final metric S(a,c) is then based on a multiplication of both previously mentioned and normalized metrics. It would be interesting to know why the authors chose to multiply the respective metrics (instead of using an average) to get S(a,c). Is it because a very low value of one metric (e.g. 0.1) prevents an “acceptable” S(a,c)-value in the case the other metric is relatively high (e.g. 0.8) (e.g. multiplication: 0.08 vs. average: 0.45)?

The Referee is correct. Multiplying the two quantities, F(a,c) and R(a,c), after normalization to the [0,1] interval, causes the final metric S(a,c) to be negligible where any of the two factors is negligible, so that no unacceptable situation arises. The procedure seems to be not only logical, as the Referee observed, but it proved to be effective in rejecting unrealistic results.

7. The usage of S(a,c) appears to be based also on the assumption that a high AUROC value is directly related to a higher quality/usability of the underlying logistic regression based model. In this context, I do not see a problem to use the calibration set to measure this metric since logistic regression models are relatively robust and do not tend to (strongly) overfit on training data. However, several studies outline potential limitations of AUROC-based measures for spatial distribution models (Frattini et al., 2010; Lobo et al., 2008; Steger et al., 2016). Therefore, I assume that there might be a risk that the conducted direct deductions (i.e. by interpreting solely the metrics) can lead to misleading conclusions. I think that a discussion of potential drawbacks of the proposed metrics (S(a,c)) would also be valuable. Frattini P, Crosta G, Carrara A (2010) Techniques for evaluating the performance of landslide susceptibility models. Engineering Geology 111:62–72. Lobo JM, Jiménez-Valverde A, Real R (2008) AUC: a misleading measure of the performance of predictive distribution models. Global Ecology and Biogeography 17:145–151. Steger S, Brenning A, Bell R, Petschko H, Glade T (2016) Exploring discrepancies between quantitative validation results and the geomorphic plausibility of statistical landslide susceptibility maps. Geomorphology 262:8–23.

We agree with the Referee. However, we strongly stress that we did not “*conducted direct deductions*”, as we *did not* make a straightforward use of the AUC_{ROC} metric, as we discussed already, but we rather produced a very different overall metric. In our opinion, this is now clear in the Introduction, throughout the manuscript, and in the Conclusions.

8. I also suggest a minor restructuring of some text parts to enhance readability and to reduce redundancies:

From my perspective, several “non-discussion-parts” of the manuscript already contain useful discussions (e.g. p8 line 28-30; p. 9 line 28f; p. 10 line 11f etc.). As a reader, I would prefer to read those text segments within a well-structured discussion, which summarizes those issues (e.g. one part may relate to the SU-segmentation, another to advances/limitations of the metrics, another to the conducted susceptibility modelling etc.). I propose to restructure and expand the discussion part (e.g. including subsections, separating discussion and conclusion).

We followed the Referee’s suggestion to expand the Discussion. We moved the conclusions to a separate section. Section 8.4 was then removed from the Manuscript, and Figure 1 was changed according to the new sections numbering.

p. 2, line 20-23: I suggest to shift these lines to section 5 (“Landslide susceptibility modelling”)

We have accepted the suggestion.

p. 13f (section 8.4): I propose to address the calculation of the combined metric S(a,c) within the methods section.

We have accepted the suggestion.

p. 14 line 15 to 20: Those sentences are similar to the text passages in p. 1 line 16-19. I recommend explaining the concept of SU solely within the introduction (p.1)

The suggested text was removed from the Discussion.

9. Figure 5: I would prefer a more intuitive colour selection for the land cover map (e.g. dark green for forests, light green for pastures, brown for arable land, blue for water etc.). Figure 10: I think that inserts of corresponding metrics (F(a,c), R(a,c), S(a,c), fraction of significant predictors) within each of those nine maps would further enhance traceability (i.e. interrelations) of the results. Maybe you can also present the susceptibility map produced by the optimal parameter combination (i.e. "a" and "c").

We have changed the colors in the Figure according to the suggestion.

10. The title clearly reflects the content of the paper. The guidelines of the journal (GMD) state that "the model name and number should be included in papers that deal with only one model." Maybe the authors can add the name of the software "r.slopeunits" to the title?

We have added the name of the software to the title, which now reads "*Automatic delineation of geomorphological slope-units with r.slopeunits v1.0 and their optimization for landslide susceptibility modelling*".

Answers to Anonymous Referee #2

The manuscript presents a complex approach to optimized hillslope partitioning designed for landslide susceptibility modeling. One of the innovative contributions of this work is the optimization of parameters - many geoprocessing methods require tuning empirical parameters so even highly automated procedures can become time consuming and subjective - this paper tries to address this issue using an iterative process along with robust statistics. The proposed approach can be adapted to other types of landform units mapping so the paper could potentially have broader impact.

The most serious issue with the paper is unclear validation or evaluation of the results. In the fig. 7 the derived hillslope units appear to have little relation to the observed landslides - I assume that landslide model would have to be applied to each unit to find out whether there would be a landslide but many observed landslides cross the hilslope unit boundaries and the size of units is not very consistent with the distribution and size of the landslides.

In this work, we did not take into account validation of the modelling results *i.e.,* no evaluation of the performance of the landslide susceptibility model was performed using e.g., a different set of landslides (temporal validation) or applying the model to a different location (spatial validation). The proposed optimization procedure is executed only in the model calibration phase of the logistic regression model, for at least two reasons. The first reason is that validation of the results would have added additional (and unnecessary for the scope of this work) complexity to the analysis; whereas the focus has to be on the slope-unit delineation and the optimization procedure. The second reason is that, from a conceptual point of view, the very purpose of the procedure "*is not to evaluate the performance of the LS classification but to help determining an optimal terrain subdivision for LS modeling, and thus before any LS model is available for proper validation*", as we write in Section 5 of our work.

Coming to the specific comment of the Referee, we stress that r.slopeunits does not require landslide information. The software only accepts numerical input and produces a well-defined output. A landslide inventory is used only in the susceptibility model. It is the optimization procedure's task to choose input parameters for r.slopeunits such that the aspect direction map is consistently segmented into domains facing well-defined directions, and that the landslide susceptibility model training stage performs well. In other words, the requirement that the final slope-unit based map contains polygons crossing landslide deposits is not implemented explicitly. We may only expect that landslide occurred within well-defined aspect domains (i.e., well-defined hillslopes), and that a good performance of the susceptibility model is associated to a slope-unit delineation that, on average, does not cut landslide deposits. The specific examples shown in Figure 7 illustrates precisely this point. The three *sample* slope-unit delineations were obtained with three different combinations of the parameters, providing slope-unit polygons of different shapes and sizes. The selection of the best delineation is not yet performed at this stage.

The paper does not show the details of how the final optimized results look like when overlayed with the observed landslides. It would be useful to at least include reference to the figure 10 center as the optimal partitioning, if I understand the text correctly. Is there any way to measure the improvement achieved by the proposed approach versus using simpler approaches such as the half-basins derived from r.watershed with optimized threshold or a raster based landslide model?

It is true that showing, or providing the optimal slope-unit based map would add value to our paper, and we have added the map to the revised version. Also, it is correct that the center box in Figure 10 turned out to be the optimal slope-unit partition, and we now acknowledge this in the Discussion section.

The Referee's comment concerning the improvement achieved by the proposed approach versus simpler approaches is pertinent only if one assumes that the half-basins produced by r.watershed can be considered mapping units fulfilling the requirements of maximization of internal homogeneity and external non-homogeneity. The partition of the terrain obtained using r.watershed depends on the accumulation threshold selected for the delineation of the first order streams. This modelling parameter is the same for the *whole area* under examination. Use of small values of the accumulation threshold results in an over-segmentation of hillslopes internally homogeneous. This can be overcome using r.slopeunits, which determines different accumulation thresholds in different regions of the study area, according to local terrain variability, quantified by aspect homogeneity. A susceptibility model based on half-basins with a single accumulation threshold would be of little conceptual meaning. For this reason, it was not calculated.

Few minor comments and questions: - the term slope units could be misleading (e.g. it could be interpreted as classes of slope steepness) - perhaps hillslope units may be better, but leave the slope units if this term is used by this journal

We decided to stick to the slope-unit name and definition, which is well known in the literature as it can be seen checking the list of references.

- the landslides were from the years 1954-77, were the contours from which the DEM was interpolated from the same time period? Were at least some of the landslides captured by the contours?

The contour lines used to prepare the DEM are more recent than the landslides. The DEM captures the morphology of the large and very large mass movements.

Implementation as a module in open source GIS makes reproducing the results easier, the authors should also provide their data set to ensure full reproducibility and comparison with other methods

We stress here that the reproducibility invoked throughout the manuscript refers to the procedure we have developed and tested, and not to the final result pertaining to the particular example presented in this work to illustrate the procedure. We claim reproducibility of the results because, unlike many existing approaches in the literature, every step is parametrized and nothing is left to expert judgement. As a result, for a given dataset and values of the input parameters, the result is uniquely determined if the r.slopeunits software is used to delineate the slope-units. We consider this a significant advantage and an advancement towards standardization.

The datasets used in this work consists of (i) a 25 x 25m DEM, (ii) a reclassified lithological map, (iii) a reclassified land use map, and (iv) a detailed landslide inventory. The datasets were obtained in collaboration with third parties, who should be consulted before the data are disclosed by any means or used for purposes different from obtaining results for a scientific publication. The mentioned data may be available upon motivated request, but adding datasets to this work would only slow down the publication process, and will not add to the content and meaning of the paper. We have added the final result of our procedure applied to our test area, the optimal slope-unit delineation, in Figure 14. The vector layer is also available upon request, should anyone be interested in comparing results obtained with other models or approaches.

List of changes in the revised version of the Manuscript

- We changed the title to comply with GMD requirements to include the name and version of the software. The abstract was left untouched.
- Following Referee #1 suggestion, we moved a brief description of the type of landslides used in the analysis from the Introduction to Section 5.
- Following Referee #1 suggestion, we removed Section 8.4 and moved the text to Section 6 (definition of the overall metric S using normalized F_o and R_o) and to the Discussion (the remaining parts).
- We distinguished the “Discussion and Conclusions” Section into two separate sections, discussing most of the issues suggested by Referee #1.
- We modified Figure 1 according to the new sections numbering.
- We modified Figure 5B according to Referee #1 suggestion.
- We added the new Figure 14, showing explicitly the final, optimal slope-unit subdivision of our test area.

Automatic delineation of geomorphological slope-units with `r.slopeunits v1.0` and their optimization for landslide susceptibility modelling

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Abstract. Automatic subdivision of landscapes into terrain units remains a challenge. Slope-units are terrain units bounded by drainage and divide lines, but their use in hydrological and geomorphological studies is limited because of the lack of reliable software for their automatic delineation. We present the `r.slopeunits` software for the automatic delineation of slope-units, given a digital elevation model and a few input parameters. We further propose an approach for the selection of optimal parameters controlling the terrain subdivision for landslide susceptibility modelling. We tested the software and the optimization approach in Central Italy, where terrain, landslide, and geo-environmental information was available. The software was capable of capturing the variability of the landscape, and to partition the study area into slope-units suited for landslide susceptibility modelling and zonation. We expect `r.slopeunits` to be used in different physiographical settings for the production of reliable and reproducible landslide susceptibility zonations.

1 Introduction

The automatic subdivision of large and complex geographical areas, or even entire landscapes, into reproducible, geomorphologically coherent terrain units remains a conceptual problem and an operational challenge. *Terrain units* (TU) are subdivisions of the terrain that maximize the within-unit (internal) homogeneity and the between-unit (external) heterogeneity across distinct physical or geographical boundaries (Guzzetti et al., 1999; Guzzetti, 2006; Komac, 2006; Saito et al., 2011; Sharma and Mehta, 2012; Fall et al., 2006; Li et al., 2012; Erener and Düzgün, 2012; Komac, 2012; Schaetzl et al., 2013; Mashimbye et al., 2014). A *Slope-unit* (SU) is a type of morphological TU bounded by drainage and divide lines (Carrara, 1988; Carrara et al., 1991, 1995; Guzzetti et al., 1999), and corresponds to what a geomorphologist or an hydrologist would recognize as a single slope, a combination of adjacent slopes, or a small catchment. This makes SU easily recognizable in the field, and in topographic base maps. Compared to other terrain subdivisions, including grid-cells or unique-conditions units (Guzzetti et al., 1999; Guzzetti, 2006), SU are related to the hydrological and geomorphological conditions and processes that shape natural landscapes. For this reason, SU are well suited for hydrological and geomorphological studies, and for landslide susceptibility (LS) modelling and zonation (Carrara et al., 1991, 1995; Guzzetti et al., 1999; Guzzetti, 2006).

SU can be drawn manually from topographic maps of adequate scale and quality (Carrara, 1988). However, the manual delineation of SU is time consuming and error prone, limiting the applicability to very small areas. Manual delineation of SU is also intrinsically subjective. This reduces the reproducibility – and hence the usefulness – of the terrain subdivision. Alternatively, SU can be delineated automatically using specialized software. The latter exploits digital representations of the terrain, typically in the form of a Digital Elevation Model (DEM) (Carrara, 1988), or adopts image segmentation approaches (Flanders et al., 2003; Dragut and Blaschke, 2006; Aplin and Smith, 2008; Zhao et al., 2012). In both cases, the result is a geomorphological subdivision of the terrain into mapping units bounded by drainage and divide lines, which can be represented by polygons (in vector format) or groups of grid-cells (in raster format).

Large and complex geographical areas or landscapes can be partitioned by different SU subdivisions. Unique (*i.e.*, "universal") subdivisions do not exist, and *optimal* (best) terrain subdivisions depend on multiple factors, including the size and complexity of the study area, the quality and resolution of the available terrain elevation data, and – most importantly – the purpose of the terrain subdivision (*e.g.*, geomorphological or hydrological modelling, landslide detection from remote-sensing images, landslide susceptibility, hazard or risk modelling). An open problem is that an optimal SU subdivision for LS modelling cannot be decided unequivocally, a priori, or in an objective way, and the quality and usefulness of a LS zonation depends on the SU subdivision (Carrara et al., 1995).

In this work, we propose an innovative modelling framework to determine an *optimal* terrain subdivision based on SU best suited for LS modelling. For the purpose, we also present the ~~new~~the `r.slopeunits` software for the automatic delineation of SU, and we propose a method to optimize the terrain subdivision in SU performed by the software. The `r.slopeunits` software is written in Python for the GRASS GIS (Neteler and Mitasova, 2007), and automates the delineation of SU, given a DEM and a set of user-defined input parameters. We tested the `r.slopeunits` software and the proposed optimization procedure for LS modelling in a large area in Central Italy, where sufficient landslide and thematic information was available to us (Cardinali et al., 2001, 2002). ~~To model LS, we considered slow to very slow moving shallow slides, deep-seated slides, and earth flows, and we excluded rapid to fast-moving landslides, including debris flows and rock falls. The `r.slopeunits` software performs the delineation of the SU, and does not perform the LS modelling. For the later, we exploit specific modelling software (Rossi et al. 2010).~~

The paper is organized as follows. ~~Fist~~First, we present the proposed approach for the delineation of an *optimal* terrain subdivision into SU best suited for LS modelling, based on an optimization method (Section 2). Next (Section 3), we present the method for the automatic delineation of SU, which we have implemented in the `r.slopeunits` software for the GRASS GIS, and (Section 4) we describe a segmentation metric useful for the evaluation of the SU internal homogeneity. Next, we introduce landslide susceptibility modelling (Section 5) and our optimization approach to the SU partitioning (Section 6). This is followed (Section 7) by a description of the study area, in Central Italy, and of the data used for LS modelling. In Section 8 we ~~discuss~~present the results obtained in our study area, in Central Italy, ~~and we conclude (Section 10) summarizing the lessons learnt, and outlining possible uses of the `r.slopeunits` software and of the optimization procedure.~~ then we summarize the obtained results (Section 9), and outline possible uses of the `r.slopeunits` software and of the optimization procedure (Section 10).

2 Modelling framework

We propose a new modelling framework for the parametric delineation of slope-units (SU) and their optimization, as a function of a few input parameters, for the specific purpose of determining landslide susceptibility (LS) adopting statistically-based classification methods (Guzzetti et al., 1999, 2005, 2006; Guzzetti, 2006; Rossi et al., 2010). The framework is exemplified in Fig. 1, and consists of the following steps:

1 First, the `r.slopeunits` SU delineation software – described in Section 3, and whose flowchart is shown in Fig. 2 – is run multiple times with different combinations of the input modelling parameters. Each software run results in a different subdivision of the landscape into a different set of SU. In each run, the number and size of the SU depend on the input modelling parameters.

2a Second, the internal homogeneity and external inhomogeneity of each SU subdivision – required by any meaningful terrain subdivision – are defined in terms of terrain aspect, measured by the circular variance of the unit vectors perpendicular to the local topography represented by all grid cells in a slope-unit. For each set of SU obtained in step 1 using different input parameters, the quality of the aspect segmentation is evaluated adopting a general-purpose segmentation objective function, presented in Section 4.

2b At the same time, for each set of SU obtained in step 1, a LS model is calibrated adopting a Logistic Regression Model (LRM) for SU classification (Section 5). In the LRM, each SU is classified as stable (*i.e.*, free of landslides) or unstable (*i.e.*, having landslides) depending on a (in our case linear) combination of the local terrain conditions (*i.e.*, the geo-environmental variables). The performance of the model calibration is evaluated using the Area Under the Curve (AUC) of Receiver Operating Characteristic (ROC), referred to as $\mathrm{AUC_{ROC}}$ metric, a standard and objective metric commonly adopted in the literature to evaluate the performance of LS models (Rossi et al., 2010).

3 Lastly, an overall (combined) objective function is defined by properly combining the segmentation (step 2a) and the $\mathrm{AUC_{ROC}}$ (step 2b) objective functions, as described in Section 6. Maximization of this quantity allows to single out the optimal set of SU (i.e., the optimal terrain subdivision) that, simultaneously, (i) provides a good aspect segmentation, and (ii) results in an effective calibration of the LS model.

4 Maximization of the combined objective function allows selecting objectively the optimal combination of the input terrain modelling parameters best suited for LS modelling (step 4 in Fig. 1) and the corresponding SU subdivision.

In summary, the proposed modelling framework relies on an optimization procedure that maximizes a proper, specific function that contains information on (i) the morphology of the study area, represented by the aspect segmentation metric (step 2a), and on (ii) the specific landslide processes under investigation (in our case slow to very slow moving shallow slides, deep-seated slides, and earth flows), represented by the LS model performance and the associated $\mathrm{AUC_{ROC}}$ metric (step 2b). The optimization approach removes subjectivity from the SU delineation algorithm, and produces a result that is objective and completely reproducible. This is a significant advantage over manual methods (Carrara, 1988), or specialized software that needs multiple parameters and specific calibration procedures.

3 Automatic delineation of slope-units

Automatic delineation of SU can be performed adopting two strategies. The first strategy defines a large number of small homogeneous areas, and enlarges or aggregates them progressively, maximizing the aspect homogeneity of the SU (Zhao et al., 2012). Following this approach, the size of the initial polygons representing the small homogeneous areas is significantly smaller than the size of the desired (final) SU, which results from the aggregation of multiple areas performed maximizing an objective function (Espindola et al., 2006). The second strategy defines an initial small number of large or very large areas, and reduces progressively their size until a satisfactory result is obtained (Carrara, 1988; Carrara et al., 1991, 1995). In the second strategy, the study area is subdivided into large sub-catchments, which can be further subdivided into left and right sides (looking downstream with respect to the main drainage), with the resulting two sides named *half-basins* (HB). The size of the initial HB is much larger than the desired size for the SU.

For both strategies, the final subdivision of the landscape into SU does not maintain memory of the terrain partitioning represented by the initial areas or HB. In both strategies, deciding when to stop the aggregation or the partitioning to obtain a terrain subdivision suitable for a specific use (in our case LS modelling) is critical. Both strategies are subject to the selection of user-defined modelling parameters, which introduce subjectivity and reduce the reproducibility of the results. These are conceptual and operational problems that hamper the design and the implementation of an automatic procedure for the effective delineation of terrain subdivisions based on SU (Carrara et al., 1995; Espindola et al., 2006; Dragut et al., 2010, 2014).

3.1 Slope-unit delineation algorithm

For the delineation of the SU, we adopt the second strategy outlined above *i.e.*, we start from a relatively small number of large HB, and we gradually reduce their size by subdividing the HB into smaller TU. Hydrological conditions and terrain aspect requirements control the subdivision of the large HB into smaller TU. The approach is adaptive, and results in a geomorphological subdivision of the terrain based on SU of different shapes and sizes that capture the real ("natural") subdivisions of the landscape.

We implemented the approach to the delineation of SU in a specific algorithm, coded in the `r.slopeunits` software (Fig. 2). The algorithm (and the software) uses the hydrological module `r.watershed` (Metz et al., 2011) available in the GRASS GIS. Using a DEM to represent terrain morphology, `r.watershed` produces a map of HB adopting an advanced flow accumulation (FA) area analysis. Each grid-cell in the DEM is attributed the total contributing area FA, based on the number of cells that drain into it. The FA values are low along the divides and increase downstream along the drainage lines. This information is used to single out streams and divides *i.e.*, the main elements bounding a SU (Carrara, 1988). The `r.watershed` module can use single (Single Flow Direction, SFD) or multiple (Multiple Flow Direction, MFD) flow direction strategies. In the SFD strategy, water is routed to the single neighbouring cell with the lowest elevation, and in the

MFD strategy water is distributed to all the cells lower in elevation, proportionally to the terrain slope in each direction. The `r.slopeunits` software adopts the MFD strategy to distribute water to the neighbouring cells.

The `r.slopeunits` software requires a DEM, `demmap`, accepts an optional layer showing alluvial plains (AP), `plainsmap`, and the following user-defined numerical parameters (A in Fig. 2): (i) the flow accumulation area (FA) threshold, `thresh`, (ii) the minimum surface area for the SU, `areamin` (in square meters), (iii) the minimum circular variance (Nichols, 2009) of terrain aspect within a slope-unit, `cvmin`, (iv) a reduction factor, `rf`, (v) the maximum surface area for the SU, `maxarea` (in square meters, optional), and (vi) a threshold value for the cleaning procedures, `cleansize` (in square meters, optional; see Section 3.2). For simplicity, in the following we refer to the numerical values of `thresh`, `areamin`, `cvmin` and `rf` as t, a, c and r, respectively.

The software adopts an iterative approach to partition a landscape into SU. In the first iteration, `r.watershed` uses the threshold t controlling the partitioning into HB. The parameter t has to be smaller than the maximum surface accumulation area (FA) for the study area to allow for the delineation of at least two HB large enough to be further subdivided. Grid-cells with FA $> t$ are recognized as drainage lines (*i.e.*, streams), and used to delineate the river network by `r.watershed`, grouping all grid-cells in the DEM that drain into a given stream segment. These cells collectively represent the catchment drained by the stream segment, which can be further subdivided into left and right HB (B in Fig. 2). A low value of the contributing (flow accumulation, FA) area t results in a dense hydrological network draining a large number of small HB, and a large value of t results in a reduced number of streams draining a smaller number of relatively large HB.

At each iteration, where a GIS layer showing alluvial plains (AP) is available, `r.slopeunits` identifies the grid-cells in the AP and excludes them from the analysis (C in Fig. 2). When the SU are exploited for the analysis of the processes causing slope instability, the exclusion is justified by the empirical observation that landslides do not occur in plain areas. The value of the `areamin` parameter a, defines the smallest possible (planimetric) area for a SU. The circular variance is defined as $1-|\boldsymbol{R}|/N_v$, in the range between 0 and 1, where N_v is the number of grid-cells in each HB and $|\boldsymbol{R}|$ is the magnitude of the vector $\boldsymbol{R}$ that results from the sum of all unit vectors describing the orientation of each grid-cell. As an example, Fig. 3A shows that a group of unit vectors dispersed 23 degrees apart, on average, is characterized by a circular variance of 0.1, and Fig. 3B shows that a group of unit vectors dispersed 62 degrees apart, on average, is characterized by a circular variance of 0.6. Thus, a value of 0.1 of the circular variance represents grid-cells facing all nearly in the same direction, whereas a value of 0.6 represents more dispersed grid-cells. In the algorithm, the circular variance is controlled by the value of the `cvmin` parameter c, affecting the homogeneity of terrain aspect in the HB. Small values of c result in more uniform HB, and large values of c in less uniform HB, in terms of terrain aspect.

At each iteration, `r.watershed` splits each existing *parent half-basin*, HB$_{parent}$ (D in Fig. 2) into nested *child half-basins*, HB$_{child}$. The average area of the HB$_{child}$ defined for each HB$_{parent}$ is checked against a. When the average area is smaller than a, the subdivision is rejected and the HB$_{parent}$ is selected as a candidate SU. When the average area is larger than a, the procedure keeps the HB$_{child}$ for the next step of the analysis. The rejection procedure prevents very small HB from being selected as candidate SU.

The next step of the procedure consists in comparing the size and circular variance of each HB_{child} with the user-defined values a and c. Where the circular variance is smaller than c, or the size is smaller than a, the HB_{child} is taken as a candidate SU (E in Fig. 2). If the user defines the optional input parameter `maxarea`, the control on the circular variance is not performed for the HB_{child} having a size larger than `maxarea`. This imposes a constraint on the maximum size of the candidate SU (not shown in E in Fig. 2). The remaining HB_{child} are fed to the next iteration of `r.watershed`, which is initialized using a smaller value of t. At the i-th iteration, the value of t depends on the value of the reduction factor r, according to $t_{i+1} = t_i - t_i/r$ (F in Fig. 2). The decrease of t_i is faster for small values of $r \geq 2$. We checked empirically that values of $r > 10$ lead to visually better results, at least in our study area. This is due to the fact that a slow decrease of t_i allows for a better (finer) control on the subdivision of the parent half-basin, HB_{parent}. On the other hand, a fast decrease obtained with r = 2 prevents the algorithm from checking if intermediate values of t_i produce candidate SU. Thus, a slow decrease in t_i results in a larger number of iterations, which produce better results at the expenses of a longer computing time required to complete the iterations.

At each iteration the HB_{child} are processed again by `r.watershed` as HB_{parent}. The iterative procedure ends when the entire study area is subdivided into candidate SU that match the user requirements, in terms of minimum area (a) and circular variance (c). In the resulting map, the size and shape of the candidate SU can be determined by the constraint of minimum surface area, or by the constraint of the minimum circular variance of the terrain aspect. The final terrain subdivision contains candidate SU whose minimum size approximates a.

The final SU partitioning is obtained after an additional (cleaning) step intended to identify and process candidate SU exhibiting unrealistic or unacceptable size or shape (G in Fig. 2). This is discussed in the next Section.

3.2 Slope-units cleaning procedure

The `r.slopeunits` software may produce locally unrealistic candidate SU, which are too small, too large, or odd shaped. As an example, in large open valleys where terrain is flat or multiple channels join in a small area, unrealistically small subdivisions can be produced. Another example is represented by unrealistically elongated or large candidate SU found along regular and planar slopes. These terrain subdivisions, although legitimate from the algorithm hydrological perspective, are problematic for practical applications and should be revised and removed, eventually. Very small candidate SU consisting of a few grid-cells are often the result of artifacts (errors) in the DEM. These candidate SU should also be removed. To remove candidate SU with unrealistic or unwanted sizes (G in Fig. 2), we have implemented three distinct software tools based on three different methods. The three methods require the user to set the `cleansize` parameter that imposes a strict constraint on the minimum possible size (planimetric area) for a slope-unit.

The first method simply removes all candidate SU smaller than `cleansize`. The adjacent candidate SU are enlarged to fill the area left by the removed units, using the `r.grow` GRASS GIS module. The second method, in addition to removing all candidate SU smaller than `cleansize`, it removes odd-shaped polygons from the set of the candidate SU. Enabled via the `-m` flag in combination with `cleansize`, the second method removes markedly elongated candidate SU, with a width smaller than two grid-cells. The third method merges small candidate SU with neighbouring ones based on the average terrain aspect. Enabled via the `-n` flag in combination with `cleansize`, the third method calculates the average terrain aspect of all the grid-cells in each small candidate SU. The average aspects of the neighboring SU are compared, and the two adjacent units exhibiting the smallest difference in average terrain aspect are merged, provided that the SU that is removed shares a significant part of its boundary with the neighboring unit. The final result is a terrain subdivision in which the vast majority of the SU has an area larger than `cleansize`. A drawback of the third method is that it is significantly more computer intensive than the other two methods, requiring longer processing times.

4 Segmentation metric

To evaluate the terrain partitioning into SU we use a simple metric originally proposed for the evaluation of the quality of a segmentation result (Espindola et al., 2006). In digital image processing, segmentation consists in the process of partitioning an image into sets of pixels, such that pixels within the same set share certain common characteristics. Here, we consider the terrain aspect grid map as an image to be segmented, and we assume that the segmentation metric proposed by Espindola et al. (2006) is appropriate to evaluate the terrain partition into SU. We base the assumption on the observation that the metric makes a straightforward evaluation of the internal homogeneity of the SU using the local aspect variance V, and the external heterogeneity of the SU using the autocorrelation index, I. The two quantities are defined as follows:

$$V = \frac{\sum_n s_n c_n}{\sum_n s_n}, \tag{1}$$

and

$$I = \frac{N \sum_{n,l} w_{nl} (\alpha_n - \overline{\alpha})(\alpha_l - \overline{\alpha})}{\left(\sum_n (\alpha_n - \overline{\alpha})^2\right)\left(\sum_{n,l} w_{nl}\right)}, \tag{2}$$

where n labels all the N SU in a given partition, s_n is the surface area of the n-th SU, c_n is the circular variance of the aspect in the n-th SU, α_n is the average aspect of the n-th SU, $\overline{\alpha}$ is the average aspect of the entire terrain aspect map, and w_{nl} is an indicator for spatial proximity, equal to unity if SU n and l are adjacent, zero otherwise. The local variance V, defined in Eq. (1), assigns more importance to large SU, avoiding numerical instabilities produced by small SU. The autocorrelation index I of Eq. (2) has minima for partitions that exhibit well-defined boundaries between different SU.

The optimal selection of the input parameters is the one that combines small V and small I. This is quantified by the following objective function (Espindola et al., 2006):

$$F(V,I) = \frac{V_{max} - V}{V_{max} - V_{min}} + \frac{I_{max} - I}{I_{max} - I_{min}}, \tag{3}$$

where $V_{min(max)}$ and $I_{min(max)}$ are the minimum (maximum) values of the quantities in Eqs. (1) and (2) as a function of the input parameters. To calculate I, we rewrite Eq. (2) to make it consistent with the terrain aspect map. The aspect map contains values in degrees, and the average values and products cannot be taken straightforwardly, and the following definitions have to be considered. The average values of the angles is a vectorial sum of unit vectors, so that

$$\bar{\alpha} = Arctan\left(\frac{\sum_j \sin\alpha_j}{\sum_j \cos\alpha_j}\right), \tag{4}$$

where the index j runs over all the grid-cells in the terrain aspect map. A similar definition holds for α_i, the average aspect inside the i-th slope-unit, if the sum in Eq. (4) is limited to the grid-cells belonging to the i-th SU. The difference $(\alpha_i - \bar{\alpha})$ should also be intended vectorially, as follows:

$$\alpha_i - \bar{\alpha} = Arctan\left(\frac{\sin\alpha_i - \sin\bar{\alpha}}{\cos\alpha_i - \cos\bar{\alpha}}\right). \tag{5}$$

Lastly, the product at the numerator of Eq. (2) is taken as the scalar product of the vectors $(\alpha_i - \bar{\alpha})$ and $(\alpha_j - \bar{\alpha})$, as follows:

$$(\alpha_i - \bar{\alpha}) \cdot (\alpha_j - \bar{\alpha}) = \cos\theta_i \cos\theta_j + \sin\theta_i \sin\theta_j\,, \tag{6}$$

where

$$\theta_i = Arctan\left(\frac{\sin\alpha_i - \sin\bar{\alpha}}{\cos\alpha_i - \cos\bar{\alpha}}\right), \tag{7}$$

$$\theta_j = Arctan\left(\frac{\sin\alpha_j - \sin\bar{\alpha}}{\cos\alpha_j - \cos\bar{\alpha}}\right). \tag{8}$$

Care must be taken in expressing angles and arcs consistently in degrees, or radians.

The segmentation metric $F(V,I)$ is a measure of the degree of fulfillment of the SU internal homogeneity requirement, and it is related only to the SU geometrical and morphological delineation. The metric can be used to define the "optimal" (best) partition of the territory in terms of aspect segmentation, by maximization of $F(V,I) = F(V(a,c), I(a,c))$ as a function of the a and c user-defined modelling parameters.

5 Landslide susceptibility modelling

Landslide susceptibility (LS) is the likelihood of landslide occurrence in an area, given the local terrain conditions, including topography, morphology, hydrology, lithology, and land use (Brabb, 1984; Guzzetti et al., 1999; Guzzetti, 2006). Various types of LS modelling approaches are available in the literature. The approaches differ – among other things – on the type of the TU used to partition the landscape, and to ascertain LS (Guzzetti et al., 1999; Huabin et al., 2005; Guzzetti, 2006; Pardeshi et al., 2013). Interestingly, instead of trying to define where landslides are not expected ((e.g., Marchesini et al., 2014)), over the last decades a lot of efforts have been spent for the prediction of the spatial probability of the slope failures. Among the many available types of TU (Guzzetti, 2006), SU have proved to be effective terrain subdivisions for LS modelling.

To model LS, we considered slow to very slow moving shallow slides, deep-seated slides, and earth flows, and we excluded rapid to fast-moving landslides, including debris flows and rock falls. The `r.slopeunits` software performs the delineation of the SU, and does not perform the LS modelling. For the later, we exploit specific modelling software (Rossi et al., 2010; Rossi and Reichenbach, 2016).

In this work, we prepare LS models adopting a single multivariate statistical classification model. For the purpose, we use a Logistic Regression Model (LRM) to quantify the relationship between dependent (landslide presence/absence) and independent (geo-environmental) variables. We use the presence/absence of landslides in each SU as the grouping (*i.e.*, dependent) variable. Adopting a consolidated approach in our study area (Carrara et al., 1991, 1995; Guzzetti et al., 1999), SU with 2%

or more of their area occupied by landslides are considered unstable (having landslides), and SU with less than 2% of the area occupied by landslides are considered stable (free of landslides). The 2% threshold value depends on the accuracy of a typical landslide inventory map (Carrara et al., 1991, 1995; Guzzetti et al., 1999; Santangelo et al., 2015). ~~We acknowledge that the selection of the 2% threshold may influence the selection of the appropriate SU subdivision, and may affect the results of the LS zonation. Examination of different thresholds is not investigated in the present work, because it is not an input parameter of the `r.slopeunits` software, and does not change the logic of the approach or the rationale behind our optimization procedure.~~ Users of the `r.slopeunits` software may select a different value for the landslide presence/absence threshold in the LRM (or any other classification model, where considered more appropriate, in different study areas, and with different input data. Numerical (*i.e.*, terrain elevation, slope, curvature, and other variables derived from the DEM), and categorical (*i.e.*, lithology and land use) variables are used as explanatory (*i.e.*, independent) variables in the LS modelling. Each SU is characterized by (i) statistics calculated for all the numerical variables, and (ii) percentages of all classes for the categorical variables.

The LS evaluation is repeated many times using different SU terrain subdivisions obtained changing the `r.slopeunits` (a, c) modelling parameters, and cleaned from small areas using the first (and simplest) method described in Section 3.2. We evaluate the performance skills of the different LS models calculating the $\mathrm{AUC_{ROC}}$ (Rossi et al., 2010). ROC curves show the performance of a binary classifier system when different discrimination probability thresholds are chosen (Fawcett, 2006). A ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) for the different thresholds. The area under the ROC curve, $\mathrm{AUC_{ROC}}$, ranging from 0 to 1, is used to measure the performance of a model classifier that in our case corresponds to the LS model.

Hereafter, we quantify the $\mathrm{AUC_{ROC}}$ metric with the $R(a,c)$ function, for each value of the a (surface area) and c (circular variance) input parameters of the `r.slopeunits` software. We stress that we use the $\mathrm{AUC_{ROC}}$ metric to evaluate the fitting performance of the LS model *i.e.*, to evaluate the ability of the LS model to fit the same landslide set used to construct the LS model (the landslide training set), and not an independent landslide validation set (Guzzetti et al., 2006; Rossi et al., 2010). This is done purposely, because the ~~scope~~purpose of the procedure is not to evaluate the performance of the LS classification but to help determining an optimal terrain subdivision for LS modeling, and thus before any LS model is available for proper validation. When an optimal SU subdivision is obtained (see Section 6), and a corresponding LS model is prepared, the prediction skills of the model can be evaluated using independent landslide information, where this is available (Guzzetti et al., 2006; Rossi et al., 2010).

In addition to the $\mathrm{AUC_{ROC}}$, which is a direct measure of the fitting/prediction performance of a binary classifier, the performance of the LRM model can be analysed in terms of how the different input variables (both numerical and categorical) contribute to the final result (Budimir et al., 2015). In the model, a p-value can be associated to each variable, and used to establish the significance of the variable in the LRM. The fraction of significant variables used by the LRM can be used to qualitatively understand the behaviour of the classification model as a function of the `r.slopeunits` software input parameters or, in turn, as a function of the average size of the SU. ~~We expect the LRM to use the input data less efficiently when the average SU size grows, resulting in a smaller number of significant input variables.~~

6 Optimization of SU partitioning for LS zonation

Once, for all the SU sets computed using different modelling parameters (*i.e.*, different a (surface area) and c (circular variance) values), (i) the SU terrain aspect segmentation metric $F(a,c)$ – that assesses how well the requirements of internal homogeneity/external heterogeneity are fulfilled – has been established (2a in Fig. 1 and Section 4 (Espindola et al., 2006)), and (ii) the performance of the individual LS models are estimated using the AUC_{ROC} metric $R(a,c)$ – that assesses the calibration skills of the LRM used for LS modelling – has also been established (2b in Fig. 1 and Section 5 (Rossi et al., 2010)), a proper objective function S that combines the aspect segmentation metric ($F(a,c)$) and the AUC_{ROC} calibration metric ($R(a,c)$) is established. Maximization of $S(a,c)$ as a function of the a (the minimum surface area of the slope-unit) and c (the slope-unit circular variance) modelling parameters allows to single out the optimal SU terrain subdivision for LS modelling in the given study area.

The reason for proposing a combination of the aspect segmentation and the AUC_{ROC} metrics in the search for an optimal terrain subdivision for LS modelling is the following. The single segmentation metric $F(a,c)$ is a measure of the degree of fulfillment of inter-unit homogeneity and intra-unit heterogeneity for a SU delineation obtained with given (a, c) values. As such, $F(a,c)$ is related only to the geometrical delineation of the SU, and does not consider the subsequent application of a LS model, the presence/absence of landslides, or any quantity other than terrain aspect. ~~Thus, if only the $F(a,c)$ metric is used to select a particular set of modelling parameters, the resulting "optimal" (best) set of SU has the only meaning of "best partition of the territory in terms of aspect segmentation". Similarly, the $R(a,c)$ metric considers solely the classification results of the LS model, and not the geometry of the single SU, some of which may be inadequate (*e.g.*, too large, too irregular, too small) for the scope of the terrain zonation. To specialize the SU delineation for the particular purpose of LS modelling, we combine the $F(a,c)$ and $R(a,c)$ metrics to obtain an "optimal" (best) set of SU that simultaneously satisfies morphological homogeneity requirements and provides a set of SU best suited for LS prediction.~~

To combine the two functions $R(a,c)$ and $F(a,c)$ into a single objective function, we normalized them to $[0,1]$ as follows:

$$R_o(a,c) = \frac{R(a,c) - R_{min}(a,c)}{R_{max}(a,c) - R_{min}(a,c)} \tag{9}$$

$$F_o(a,c) = \frac{F(a,c) - F_{min}(a,c)}{F_{max}(a,c) - F_{min}(a,c)}. \tag{10}$$

The functions $R_o(a,c)$ and $F_o(a,c)$are then be multiplied to obtain the final objective function $S(a,c)$,

$$S(a,c) = R_o(a,c)\,F_o(a,c)\,, \tag{11}$$

which embodies information on the quality of the terrain aspect map segmentation and on the performance of the LS model in a consistent, objective and reproducible way. The function $S(a,c)$ assumes values in the range $[0,1]$: the larger the value the better the SU partitioning in terms of (i) SU internal homogeneity and external heterogeneity, and (ii) suitability of the subdivision for LS zonation, in our study area.

7 Test area

We tested our proposed modelling framework for the delineation of SU, and for the selection of the optimal modelling parameters for LS assessment, in a portion of the Upper Tiber River basin, Central Italy (Fig. 4A). In the 2,000 km^2 area, elevation ranges from 175 m to 1571 m, and terrain gradient from almost zero along the river plains, to more than 70^o in the mountains and the steepest hills. Four lithological complexes, or groups of rock units (Cardinali et al., 2001), crop out in the area, including: (i) sedimentary rocks pertaining to the Umbria–Marche sequence, Lias to lower Miocene in age, (ii) rocks pertaining to the Umbria turbidites sequence, Miocene in age, (iii) continental, post-orogenic deposits, Pliocene to Pleistocene in age, and (iv) alluvial deposits, recent in age. Each lithological complex comprises different sedimentary rock types varying in strength from hard to weak and soft rocks. Hard rocks are massive limestone, cherty limestone, sandstone, travertine, and conglomerate. Weak rocks are marl, rock-shale, sand, silty clay, and stiff over-consolidated clay. Soft rocks are clay, silty clay, and shale. Rocks are mostly layered and locally structurally complex. Soils in the area reflect the lithological types, and range in thickness from less than 20 cm where limestone and sandstone crop out along steep slopes, to more than 1.5 m in karst depressions and in large open valleys.

To model LS, we use a digital representation of the terrain elevation, an inventory of known landslides, and relevant geo-environmental information. We use a DEM with a ground resolution of 25 m $\times$ 25 m obtained through linear interpolation of elevation data along contour lines shown on 1:25,000 topographic base maps (Cardinali et al., 2001) (Fig. 4A). The landslide inventory (Fig. 4B) was obtained from the visual interpretation of multiple sets of aerial photographs flown between 1954 and 1977, aided by field surveys, review of historical and bibliographical data, and geological, geomorphological and other available landslide maps (Cardinali et al., 2001; Galli et al., 2008; Guzzetti et al., 2008; Alvioli et al., 2014). To prepare the LS model we considered only the shallow slides, the deep-seated slides, and the earth flows. These landslides are (i) slow to very slow moving failures, and (ii) they typically remain in the slope (*i.e.*, the slope-unit) where they occur. For the deep-seated landslides and the earth flows, the landslide source (depletion) area and the deposit were considered together. This is a standard approach in modelling LS for these types of landslides. We excluded from the LS modelling all the rapid to fast-moving landslides, including debris flows and rock falls that may travel outside the slope (*i.e.*, the slope-unit) where they form.

We obtained lithological information (Fig. 5A) from available geological maps, at 1:10,000 scale (Regione Umbria), prepared in the framework of the Italian national geological mapping project CARG and in other regional geological mapping projects. The original maps, in vector format, were edited to eliminate and reclassify polygons coded as landslide deposits or debris flow deposits, and to reclassify the original 186 geologic formations and 20 cover types in five lithological complex, or lithological domains (Table 2). Definition of the five lithological complexes was made on the basis of the characteristics of the rock types (carbonate, terrigenous, volcanic, post-orogenic sediments) and the degree of competence or composition of the different geological units (massive, laminated sandstone/pelitic-rock ratio). Applying these criteria, the original 206 geological units were grouped in 17 lithological units. We obtained information on land cover from a map, at 1:10,000 scale (Regione Umbria), prepared through the visual interpretation of colour aerial photography at 1:13,000 scale, acquired in 1977 (Fig. 5B).

The map contains 13 land cover classes, of which the most common are forest (42%), arable land (31%), meadow and pasture (10%), built up areas (10%), and vineyards, live trees and orchards (6%).

The study area (Fig. 4) corresponds to an "alert zone" used by the Italian national Department for Civil Protection to issue landslide (and flood) regional warnings. The boundary of the alert zone is partly administrative, and does not correspond locally to drainage and divides lines. As a result, our SU partitioning intersects locally the boundary of the alert zone. For convenience, for our analysis we considered only SU that fall entirely within the alert zone. As a drawback, the extent of the study area varies slightly depending on the combination of the selected a and c parameters. We maintain that this has a negligible effect on the final modelling results.

8 Results

8.1 Slope-units delineation

In the study area, we ran the `r.slopeunits` software for 99 different combinations of user-defined input parameters, resulting in 99 different terrain subdivisions. In the iterative procedure (Fig. 2), the initial FA threshold (t) area and the reduction factor (r) control the numerical convergence, and do not have an explicit geomorphological meaning. On the other hand, the minimum area (a) and the circular variance (c) determine the size and control the aspect of the SU. For the analysis, we selected a large value for the FA area ($t = 5 \times 10^{6}$ m^2) keeping it constant for all the different model runs. The large value was chosen to obtain large initial HB that could be further subdivided into smaller SU by the iterative procedure (see Section 4). The value is also consistent with (*i.e.*, substantially larger than) (i) the size of the average SU used to partition the same area in a different LS modelling effort (Cardinali et al., 2001, 2002), and (ii) the average area of the considered landslides (shallow slides, the deep-seated slides, and the earth flows) in the study area (Guzzetti et al., 2008). Selection of the reduction factor (r = 10) was heuristic, and motivated by the fact that this figure provided stable results compared to those obtained using larger values. The two most relevant parameters, the minimum area a, and the circular variance c, were selected from broad ranges: a = 10,000, 25,000, 50,000, 75,000, 100,000, 125,000, 150,000, 200,000, and 300,000 m^2, and $0.1 < c < 0.6$, at evenly spaced values with an increment of 0.05. For all the `r.slopeunits` model runs, we used the same value for `cleansize` = 20,000 m^2, to remove candidate SU with area < 20,000 m^2 using the first (and simplest) of the three methods described in Section 3.2.

Fig. 6 shows nine of the 99 results of the terrain subdivisions obtained using different combinations of the a and c modelling parameters. The map in the upper left (lower right) corner shows the finest (coarsest) SU partitioning, determined using small (large) values of a and c. The map in the centre was obtained using intermediate values for the two user-defined modelling parameters. For a limited portion of the study area, Fig. 7 shows different partitioning results. In particular, Figs. 7A and 7B show the overlay of the three different partitions with the landslide inventory map (Fig. 4), using a 2- and 3-dimensional visualization, respectively, and a shaded image relief of the terrain, whereas Figs. 7C, 7D and 7E show separately the same partitions using a 3-dimensional representation. Visual inspection of Figs. 7A, 7B and 7C reveals that the coarser subdivision (c = 0.60 and a = 0.3 km^2), shown in blue, defines large SU characterized by heterogeneous orientation (aspect) values. On the other hand, the finest SU subdivision (shown in green in Figs. 7A, 7B and 7E) obtained using c = 0.10 and a = 0.01 km^2, is too small to include completely many of the landslides (shown in yellow). The combination that uses intermediate values $c = 0.35$ and $a = 0.15$ km^2 resulted in the SU subdivision shown in red in Figs. 7A, 7B and 7D.

Fig. 8 shows the effect of different combinations of a and c on the average SU size. The average area of the SU increases significantly with c (less homogeneous, more irregular slope), and it is less sensitive to the increment of a (Fig. 8A). The effect of c becomes predominant in Fig. 8B. The standard deviation of the area of the SU varies significantly with c, highlighting that larger values of c increase the average and the variability of the SU size (Figs. 8A and 8B, respectively).

8.2 Segmentation metric

For each of the 99 terrain subdivisions obtained using the procedure described above, we calculated the segmentation objective function value given by Eq. (3). The segmentation metric $F(a,c)$ (Fig. 9) is a measure of the performance of our SU delineation algorithm, and an assessment of how well the requirements of internal homogeneity/external heterogeneity are fulfilled by the procedure, as a function of a and c (2a in Fig. 1, Section 4). Where the SU are relatively small, their degree of internal homogeneity is large, but the requested heterogeneity between adjacent units is not fulfilled, completely. Where the SU are large, the requested internal homogeneity is not fulfilled entirely, because in each SU the aspect variability is large. The analysis of the $F(a,c)$ values in Fig. 9 suggests that SU subdivisions obtained using c smaller than about 0.2 and a smaller than about 50,000 m^2, or c larger than about 0.5, should not be considered in the analysis, because they are too small or too large to satisfy the aspect variability requirement.

8.3 Landslide susceptibility modelling

For each of the 99 SU delineations, we prepared a different LS zonation using a Logistic Regression Model (Section 6) adopting the modelling scheme described by Rossi et al. (2010); Rossi and Reichenbach (2016). Fig. 10 shows the results obtained for nine (out of 99) combinations of the a and c parameters. For each of the 99 susceptibility assessments, we evaluated the fitting (calibration) performance of the models computing $\mathrm{AUC_{ROC}}$ (Rossi et al., 2010), and Fig. 11 shows the obtained $\mathrm{AUC_{ROC}}$ as a function of the a and c parameters (Section 5).

The larger values of $\mathrm{AUC_{ROC}}$ were obtained for LS zonations based on SU partitions resulting from large values of c and a. Such combinations may result locally in SU with extremely large internal heterogeneity. Signatures of the heterogeneity within very large slope-units can be found both in the segmentation metric and in the LRM model results. In the segmentation metric case this is very straightforward since the values of $F(a,c)$, which is a direct measure of the slope aspect homogeneity within SU, clearly decrease with increasing values of a and c, as shown in Fig. 9. Very large SU, however, are not only heterogeneous in terms of terrain aspect, but also in terms of the morphometric and thematic variables used as input of the LRM. This is reflected in the number of input variables that significantly contribute to the susceptibility model results, as a function of a and c. We computed the number of statistically significant variables in each realization of the LRM (*i.e.*, the variables with a p–value < 0.05). Fig. 12 shows that the number of significant variables ranges from 5% (of the 50 morphometric and thematic variables) for large SU, to 35% for small SU. From this analysis we observe that for very large slope units, only very few variables are effectively used by the LRM. A more detailed analysis reveals that, in our test case, lithological variables significantly control the results, whereas other local settings (*e.g.* terrain slope) are neglected. The relevant variables are typically the terrigenous sediments and carbonate lithological complexes, where landslides are expected and not expected, respectively. As a result, in the region of large (a, c) parameters, even if we obtain high values of AUC_{ROC}, the LRM can be replaced by a simple heuristic analysis of the lithological map. The fine details of the remaining input variables are lost and a multivariate statistical approach is of little use. We clarify that to evaluate the model performance, any statistical metric based on the comparison of observed and predicted data (*e.g.* confusion matrices and derived indexes), would exhibit the same or similar trend as the AUC_{ROC} as a function of the SU size.

~~8.4 Optimization of the SU partition for LS modelling~~

9 Discussion ~~and Conclusions~~

~~Compared to other terrain subdivisions, slope-units (SU) are a type of morphological terrain unit bounded by drainage and divide lines, well related to the natural (*i.e.*, geological, geomorphological, hydrological) processes that shape and characterize natural slopes. This makes SU easily recognizable in the field or in topographic base maps, and well suited for environmental and geomorphological analysis, and in particular for landslide susceptibility (LS) modelling and zonation.~~

We have run the `r.slopeunits` software with a significant number of combinations (99) of the (a, c) input parameters, and a corresponding number of realizations of the LS model. Results showed that new `r.slopeunits` software was capable of capturing the morphological variability of the landscape, and to partition the study area into SU subdivisions of different shapes and sizes well suited for LS modelling and zonation. As a matter of fact, ~~D~~depending on the type of landslides, the scale of the available DEM, the morphological variability of the landscape, and the purpose of the zonation, the detail of the terrain subdivision may vary. A detailed terrain partitioning, with many small SU, is required to capture the complex morphology of badlands, or to model the susceptibility to small and very small landslides (*i.e.* soil slips). A coarse terrain subdivision is best suited for modelling the susceptibility of very old and very large, deep-seated, complex and compound landslides. Coarse subdivisions can also be used to model the susceptibility to channelled debris flows that travel long distances from the source areas to the depositional areas. Subdivisions of intermediate size may be required for medium to large slides and earth flows (Carrara et al., 1995). By tuning the set of user defined model parameters, `r.slopeunits` can prepare SU terrain subdivisions for LS modelling in different geomorphological settings.

Concerning the LS model, we acknowledge that our selection of the 2% presence/absence threshold may influence the production of the appropriate SU subdivision, and may affect the results of the LS zonation. Examination of different thresholds is not investigated in the present work, because it is not an input parameter of the `r.slopeunits` software, and does not change the logic of the approach or the rationale behind our optimization procedure.

We clarify that the subdivisions produced by `r.slopeunits` using different (a, c) parameters are nested *i.e.*, the boundaries of a coarse resolution subdivision encompass the boundaries of intermediate and finer subdivisions (see C, D, E in Fig. 7). This is a significant operational advantage where landslides of different sizes and types coexist, posing different threats and requiring multiple and combined susceptibility assessments, each characterized by a different terrain subdivision (Carrara et al., 1995). Optimal values of the (a, c) parameters have to be determined to obtain the best SU subdivision for a particular goal, in our case, LS modelling. We defined a custom objective function $S(a,c)$ to determine such optimal values. $S(a,c)$ is the product of a segmentation quality measure, $F(a,c)$, and LS model performance in calibration, $R(a,c)$. If only the $F(a,c)$ metric is used to select a particular set of modelling parameters, the resulting "optimal" (best) set of SU has the only meaning of "best partition of the territory in terms of aspect segmentation". Similarly, the $R(a,c)$ metric considers solely the classification results of the LS model, and not the geometry of the single SU, some of which may be inadequate ($e.g.$, too large, too irregular, too small) for the scope of the terrain zonation. Values of $F(a,c)$ indicate that there are combinations of the c and a parameters that result in SU subdivisions that do not satisfy the user requirements in terms of SU internal homogeneity and external heterogeneity (Fig. 8) (Section 8.2). On the other hand, the $\mathrm{AUC_{ROC}}$ metric increases with the average size of the SU (Fig. 11) (Section 8.3). To select the optimal terrain partitioning for LS zonation in our study area, we exploit the objective function $S(a,c)$, which simultaneously quantifies (Section 6): (i) the SU internal homogeneity and external heterogeneity (Fig. 13)A, and (ii) the (fitting) performance of the LS model (Fig. 13A). Maximization of $S(a,c)$ (Fig. 13B) provides the best combination of the (a, c) modelling parameters for a terrain subdivision optimal for LS modelling, in our study area.

In addition to the $\mathrm{AUC_{ROC}}$, we have analysed the performance of the LRM model by studying the fraction of significant variables used by the LRM, to qualitatively understand the behaviour of the classification model as a function of the `r.slopeunits` software input parameters or, in turn, as a function of the average size of the SU. The LRM is expected to use the input data less efficiently when the average SU size grows, resulting in a smaller number of significant input variables, which is indeed what we observed. This is due to the LRM inability to discriminate between input variables when the SU are too large, since each unit usually contains all the possible values of the variables: using less data makes it easier for the LRM model to produce a high-$\mathrm{AUC_{ROC}}$ result, which does not necessarily correspond to the optimal SU set. The complication is removed using the $S(a,c) = F_o(a,c)\,R_o(a,c)$ function, whose $F(a,c)$ component prevents unrealistic SU sets (both large and small) to have a high overall score.

The function $S(a,c)$ (Fig. 13B), calculated in our test case for different combinations of the a and c modelling parameters, has a maximum value at a = 150,000 m^2 and c = 0.35. The set of SU that corresponds to the optimal combination of the modelling parameters can be singled out as our "optimal" (best) result. The LS results corresponding to the optimal combination was already shown in the central box of Fig. 10, and the optimal SU map is presented in Fig. 14.

10 Conclusions

Despite the clear advantages of SU over competing mapping units for LS modelling (Guzzetti, 2006), inspection of the literature reveals that only a small proportion (8%) of the LS zonations prepared in the last three decades worldwide was performed using SU (Malamud et al., 2014). The limited use of SU for LS modelling and zonation is due – among other factors – to the unavailability of readily available, easy to use software for the accurate and automatic delineation of SU, and to the intrinsic difficulty in selecting $a\ priori$ the appropriate size of the SU, for proper terrain partitioning in a given area.

To contribute to fill this gap, we developed new software for the automatic delineation of SU in large and complex geographical areas based on terrain elevation data (*i.e.*, a DEM) and a small number of user defined parameters. We further proposed and tested a procedure for the optimal selection of the user parameters, ~~through the production of a significant number (99) of realizations of the LS model. We tested the software and the optimization procedure~~ in a 2,000 km^2 area in Umbria, Central Italy.

We expect that the `r.slopeunits` software will be used to prepare terrain subdivisions in different morphological settings, contributing to the preparation of reliable and robust LS models and associated zonations. We acknowledge that further work is required to investigate the optimization of SU partitions for different statistically-based tools used in the literature for LS modelling and zonation ($e.g.$, discriminant analysis, neural network). Guzzetti et al. (2012) have argued that lack of standards hampers landslide studies. This is also the case for the production of landslide susceptibility models and associated maps. We expect that systematic use of the modelling framework proposed in this work (Fig. 1, Section 2) and of the `r.slopeunits` software for the objective selection of the user defined modelling parameters, will contribute to the production of more reliable landslide susceptibility models. It will also facilitate the meaningful comparison of landslide susceptibility models produced $e.g.$, in the same area using different modelling tools, or in different and distant areas using the same or different modelling tools.

Finally, we argue that the proposed modelling framework and the `r.slopeunits` software are general and not site or process specific, and can be used to prepare terrain subdivisions for scopes different from landslide susceptibility mapping, including $e.g.$, definition of rainfall thresholds for possible landslide initiation, distributed hydrological modelling, statistically-based inundation mapping, and the detection and mapping of landslides and other instability processes from satellite imagery.

11 Code Availability

The code `r.slopeunits` is free software under the GNU General Public License (>=v2). Details about the use and redistribution of the software can be found in the file https://grass.osgeo.org/home/copyright/ that comes with GRASS GIS. The software and a short user manual can be downloaded at http://geomorphology.irpi.cnr.it/tools/slope-units

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Appendix A1 - Notation

In Table 1 we list the main variables and the acronyms used in the text.

Table 1. Main variables and acronyms used in the text.

Variable	Explanation	First introduced	Dimensions
a	minimum surface area for the SU	Section 3.1	m^2
c	minimum circular variance	Section 3.1	–
r	reduction factor	Section 3.1	–
t	flow accumulation threshold	Section 3.1	m^2
I	Autocorrelation index	Eq. (1)	–
V	Local aspect variance	Eq. (2)	–
$F(V, I)$	Aspect segmentation metric, also $F(a, c)$	Eq. (3)	–
$R(a, c)$	AUC_{ROC} metric for LRM calibration	Section 3.1	–
$S(a, c)$	Combined segmentation & AUC_{ROC} metric	Eq. (11)	–

Acronym	Explanation
AP	Alluvial Plain
AUC	Area Under the Curve
DEM	Digital Elevation Model
FA	Flow Accumulation
FPR	False Positive Rate
GIS	Geographical Information System
HB	Half Basin (left and right portion of a slope unit)
LRM	Logistic Regression Model
LS	Landslide Susceptibility
MFD	Multiple Flow Direction
ROC	Receiver Operating Characteristic
SFD	Single Flow Direction
SU	Slope Unit, a morphological terrain unit bounded by drainage and divide lines
TPR	True Positive Rate
TU	Terrain Unit, a subdivision of the terrain

Complex			Code
Carbonate	Massive Layers		CC1
	Thin Layers		CC2
	Marl, Calcareous Marl		CC3
Terrigenous	Massive Sandstone		CT1
	Variable SD/P fraction	Thick Layers	CT21
		Medium Layers	CT22
		Thin Layers	CT23
	Marly, SD/P<<1	Stratified	CT31
Post-Orogenic	Conglomerate, Gravel, Pebble		CPO2
	Sand		CPO3
	Silt and Clay		CPO4
	Variable CO/S/G fraction		CPO24
Others	Olistostrome		OLI
Quaternary Deposit	Alluvial Deposit		A
	Debris Cone		QDF
	Red Soil in Karstic Landscape		TRDC
	Travertine		T

Table 2. Lithological codes used in Fig. 5. SD = sandstone, P = pelitic rock, CO = conglomerate, S = sand, G = clay (Regione Umbria).

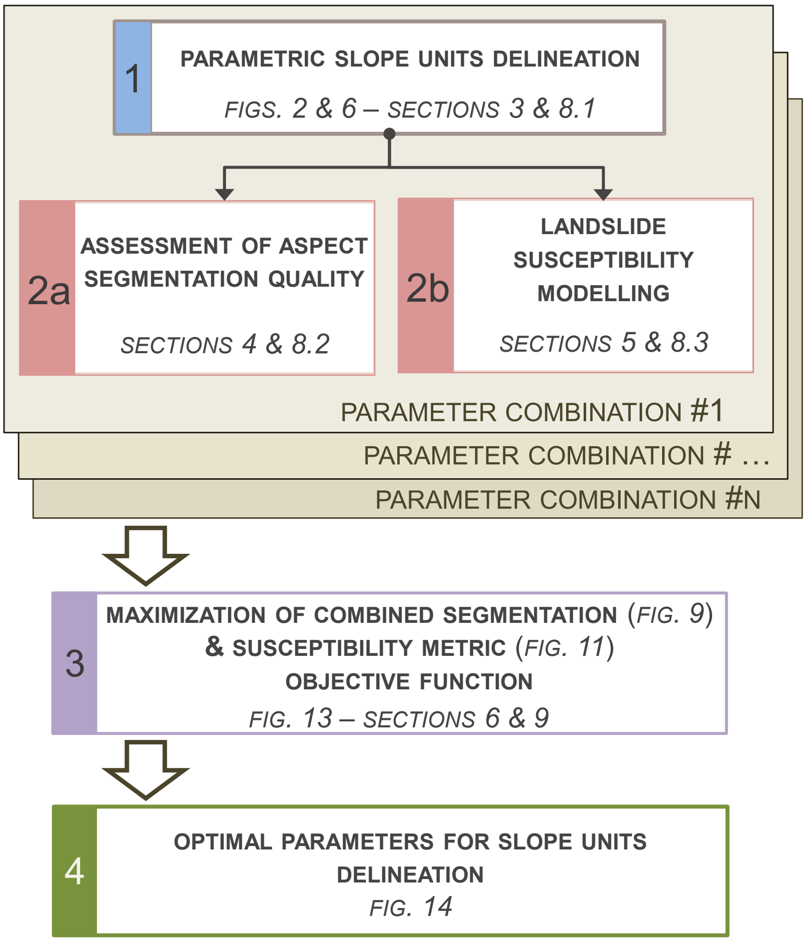

Figure 1. Logical framework for the proposed method for (1) the parametric delineation of slope-units (SU), (2a) the assessment of the quality of terrain aspect segmentation using of a proper segmentation objective function, (2b) the calculation and assessment of the quality of the landslide susceptibility (LS) modelling using a standard metric (the Area Under the Curve of Receiver Operating Characteristic – AUC_{ROC} metric), and (3) the definition and maximization of a combined objective function for (4) the determination of optimal parameters for the delineations of slope-units (SU) beste suited for landslide susceptibility (LS) modelling and zonation.

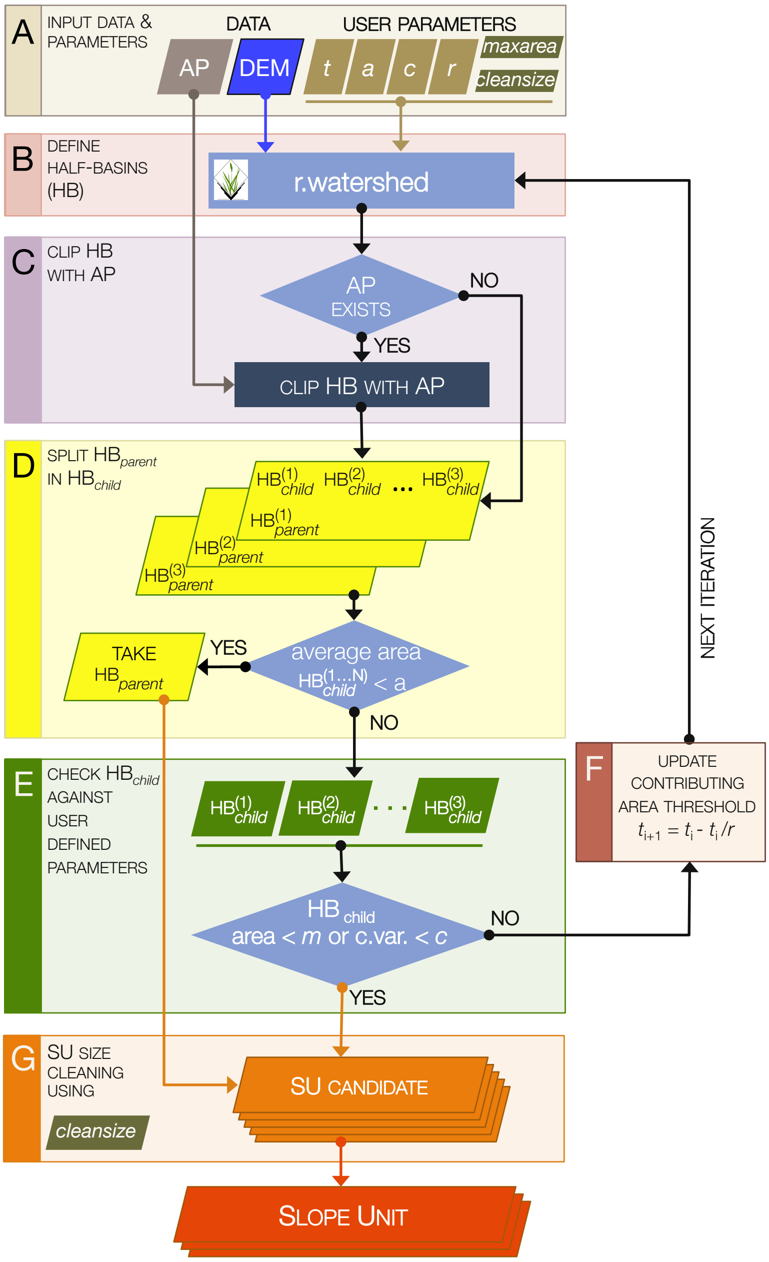

Figure 2. Flowchart for the `r.slopeunits` software. (A) Input data and parameters. AP, (input parameter name: `plainsmap`) map showing plain areas to be excluded from the processing; DEM, (`demmap`) digital elevation model; t, (`thresh`) initial FA threshold area; a, (`areamin`) minimum area; c, (`cvmin`) circular variance ; r, (`rf`) reduction factor; `maxarea`, maximum SU area; `cleansize`, size of candidate SU to be removed; see text for detailed explanation. (B) `r.watershed` processing in GRASS GIS (Neteler and Mitasova, 2007). (C) Tests if the produced HB are in a plain area. (D) The average area of new HB$_{child}$ in each HB$_{parent}$ is checked against a. (E) HB$_{child}$ are individually checked against a and c requirements. (F) The process proceeds to iteration $i+1$ for those HB$_{child}$ that still do not meet the requirements, with an updated $t_{i+1} = t_i - t_i/r$ FA threshold. (G) Small polygons are removed from the candidate SU set.

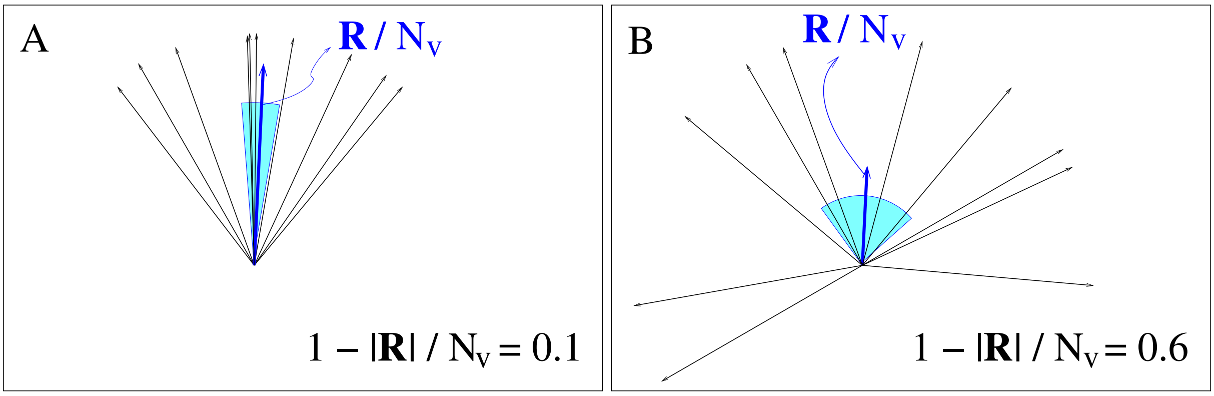

Figure 3. Graphical representation of the circular variance of terrain aspect, $1 - |\boldsymbol{R}|/N_v$. Two groups of unit vectors are shown. The unit vectors represent the local direction of terrain aspect for each grid-cell, resulting in circular variance (A) of 0.1 and (B) of 0.6. Unit vectors are perpendicular to the local topography, represented by the grid-cell.

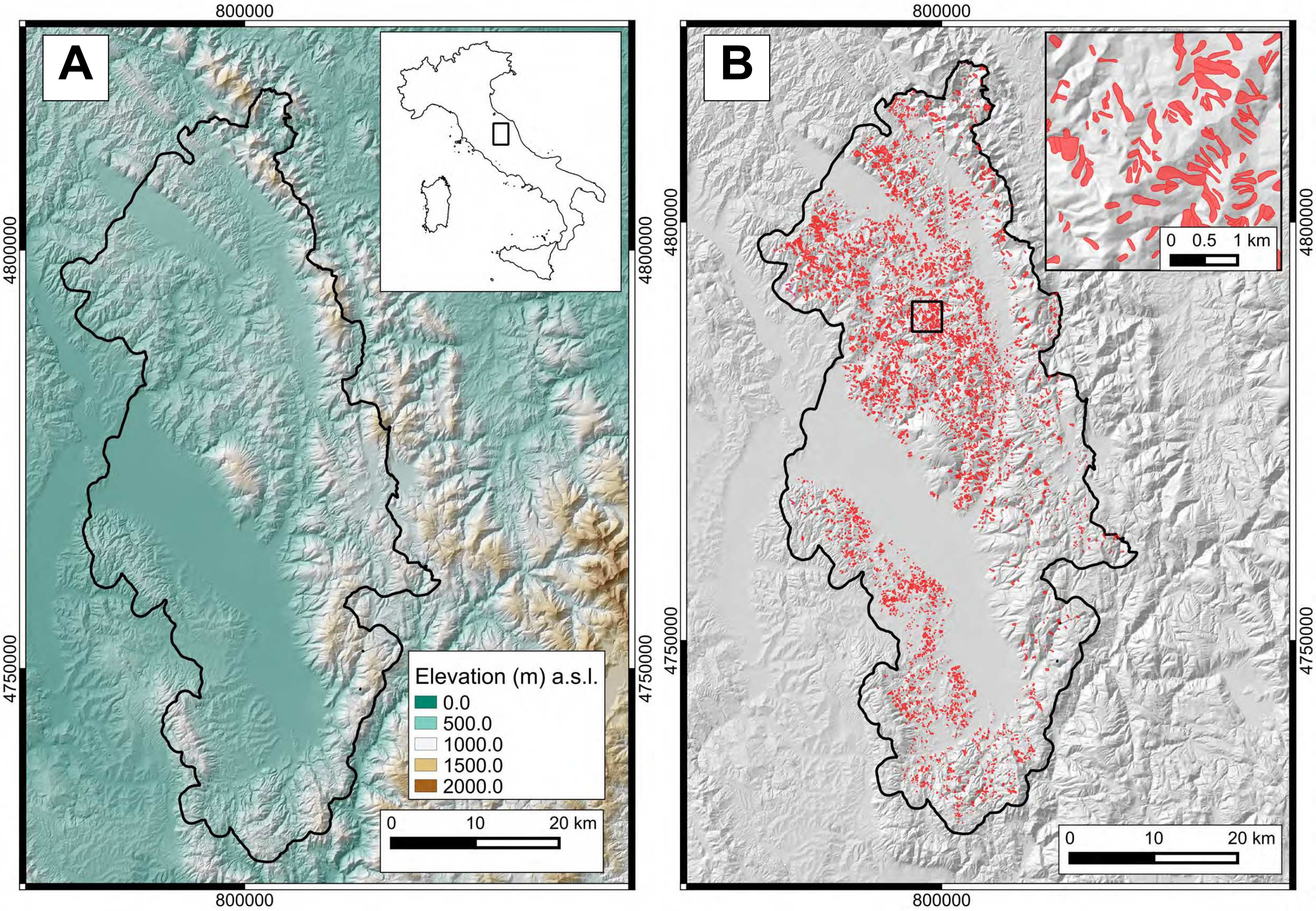

Figure 4. (A) Shaded relief image of the study area located on the Upper Tiber River basin, Umbria, Central Italy. Shades of green to brown show increasing elevation. Inset shows location of the study area in Italy. (B) Landslide inventory map (Cardinali et al., 2001). Inset shows the detail of the landslide mapping. Landslides (shown in red) were used to prepare the landslide susceptibility zonations shown in Fig. 10. The maps are in the UTM zone 32, datum ED50 (EPSG:23032) reference system.

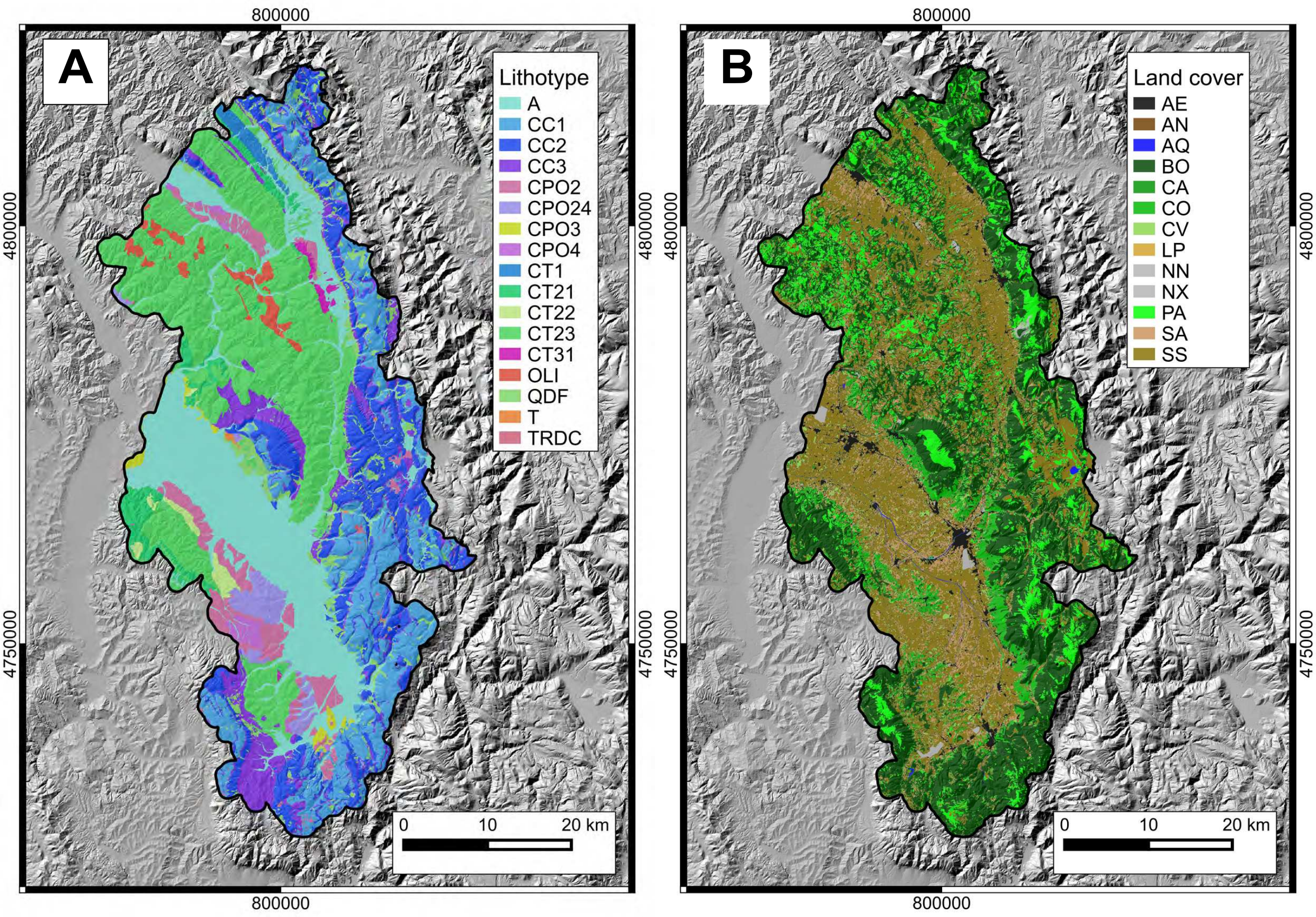

Figure 5. (A) Lithological map of Upper Tiber River basin, Umbria, Central Italy (Regione Umbria). Details of the lithological types are given in Table 2. (B) Land use map of the study area. Legend: AE: urban area, AN: bare soil, AQ: water, BO: forest, CA: orchard, CO: olive grove, CV: vineyard, LP: poplar trees, NN/NX: unclassified, PA: meadow/pasture, SA: treed seminative, SS: simple seminative. The maps are in the UTM zone 32, datum ED50 (EPSG:23032) reference system.

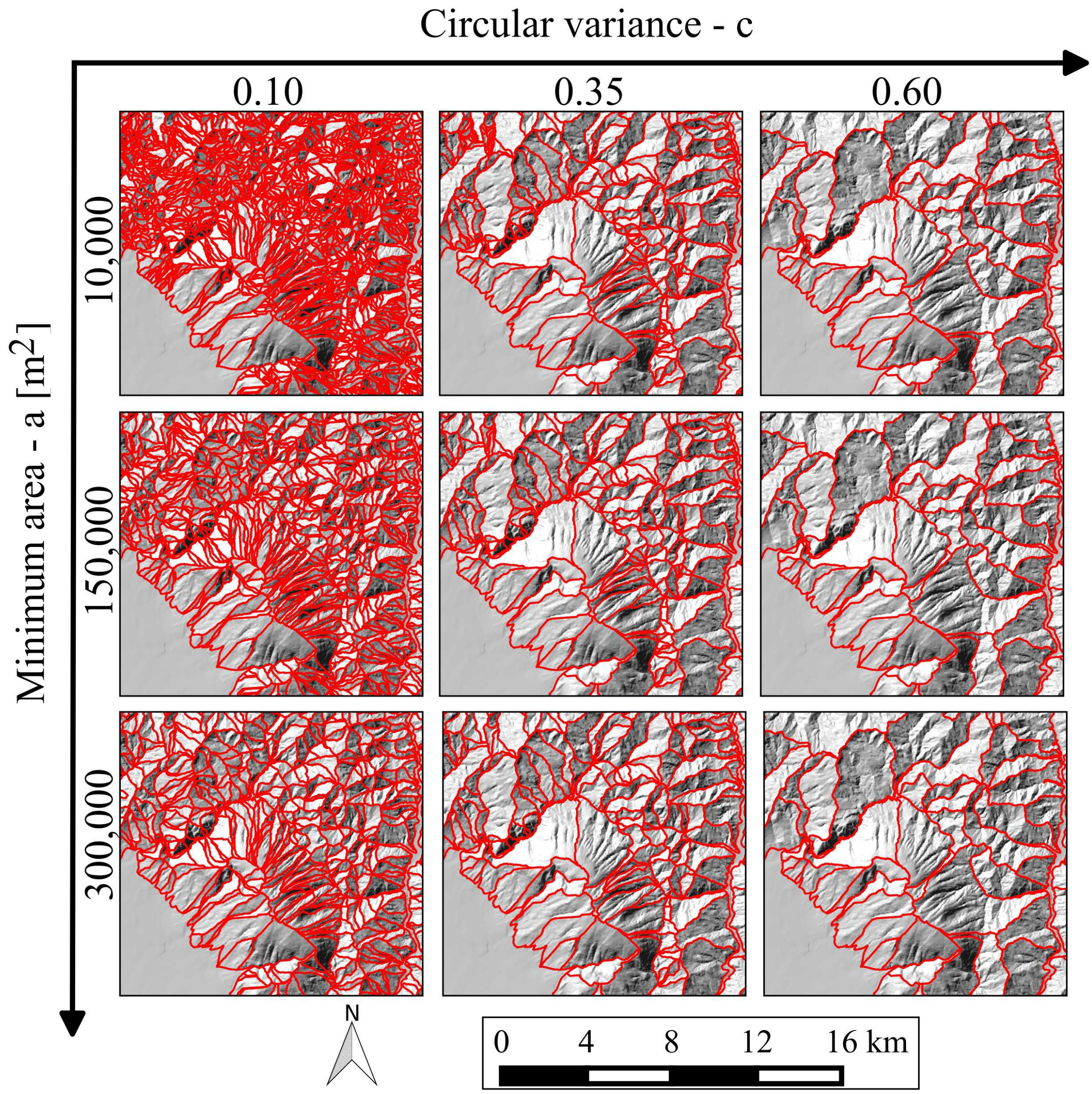

Figure 6. Nine (out of 99) slope-units (SU) terrain subdivisions for a portion of the study area. The SU were obtained changing the a and c parameters used by the `r.slopeunit` software. The maps are in the UTM zone 32, datum ED50 (EPSG:23032) reference system.

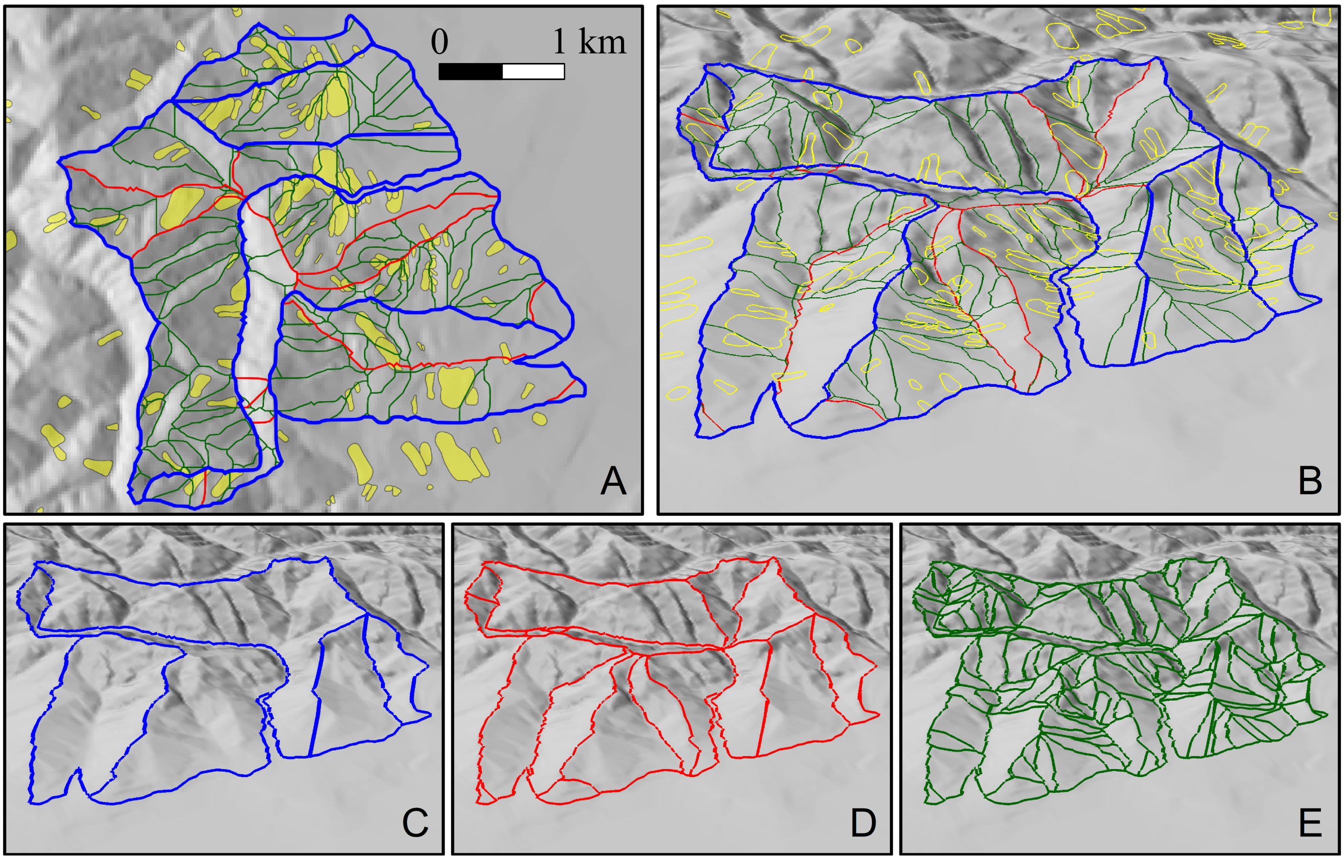

Figure 7. Example of subdivisions into slope-units (SU) for a portion of the study area. Legend: Blue, red, and green lines show boundaries of SU of increasing density and corresponding decreasing average size. Yellow areas are landslides. The five maps show the same area in plan view (A) and in perspective view (B, C, D, and E).

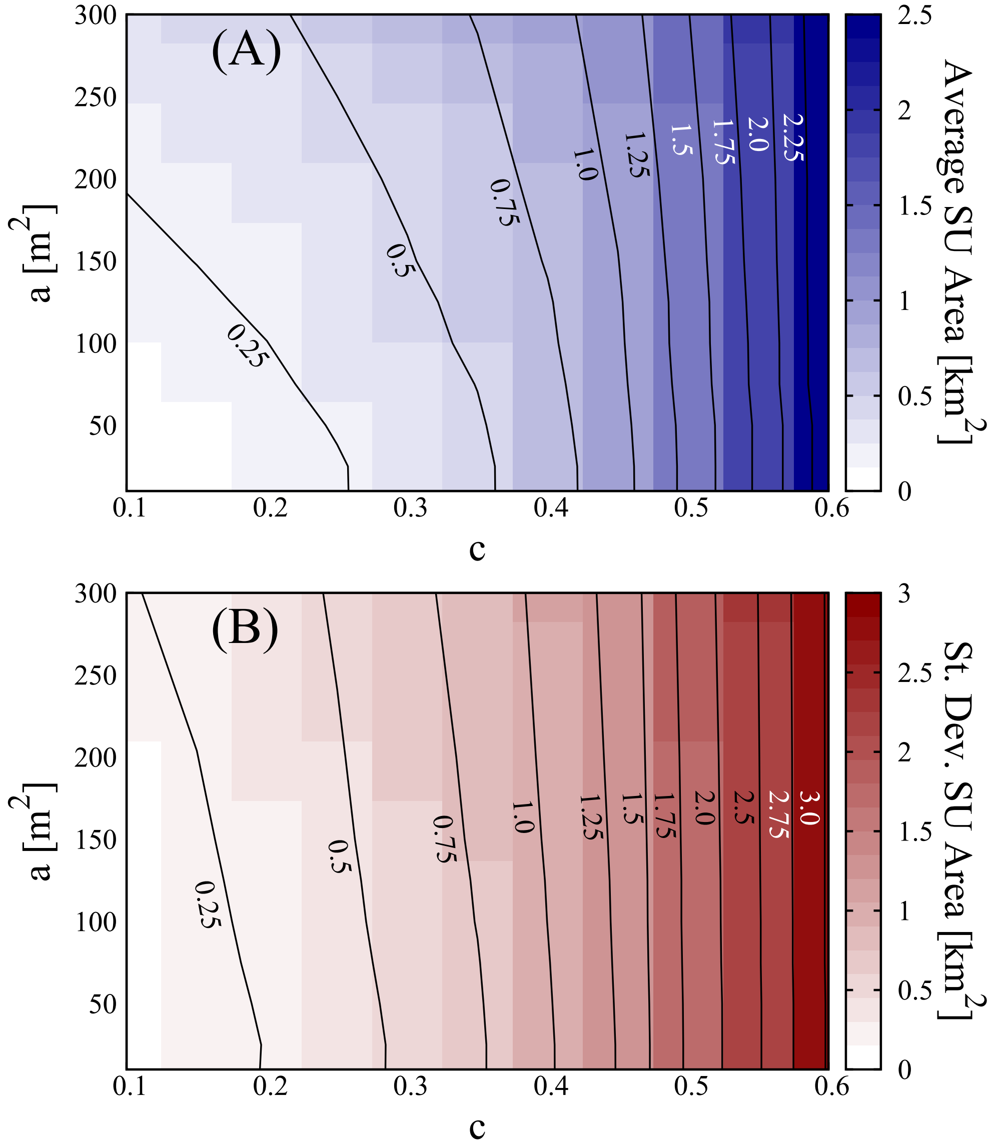

Figure 8. (A) Average and (B) standard deviation of the size of the slope-units (SU), for different combinations of a and c parameters. The minimum size of the SU is fixed by the a parameter, and the maximum size of the SU is independent of a.

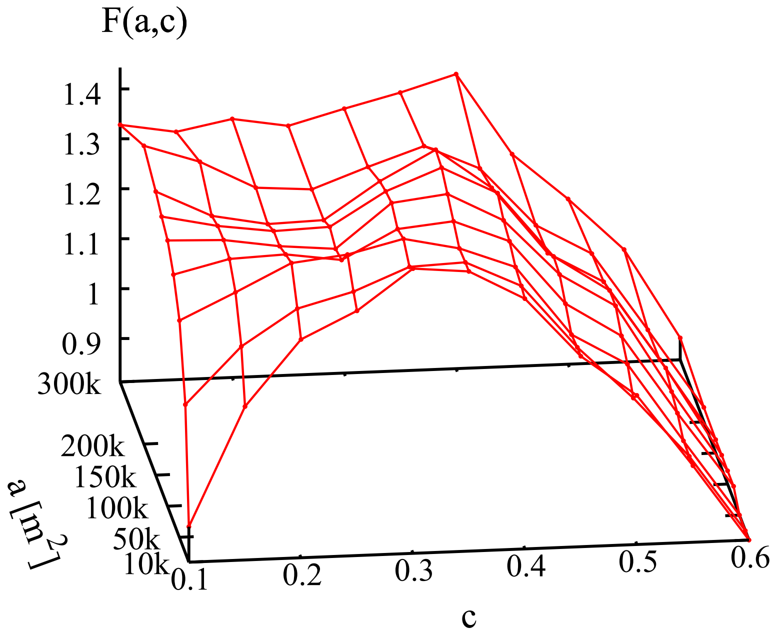

Figure 9. Segmentation objective function values (Eq. (3)) calculated for 99 slope-units (SU) partitions obtained using different combinations of the a and c parameters.

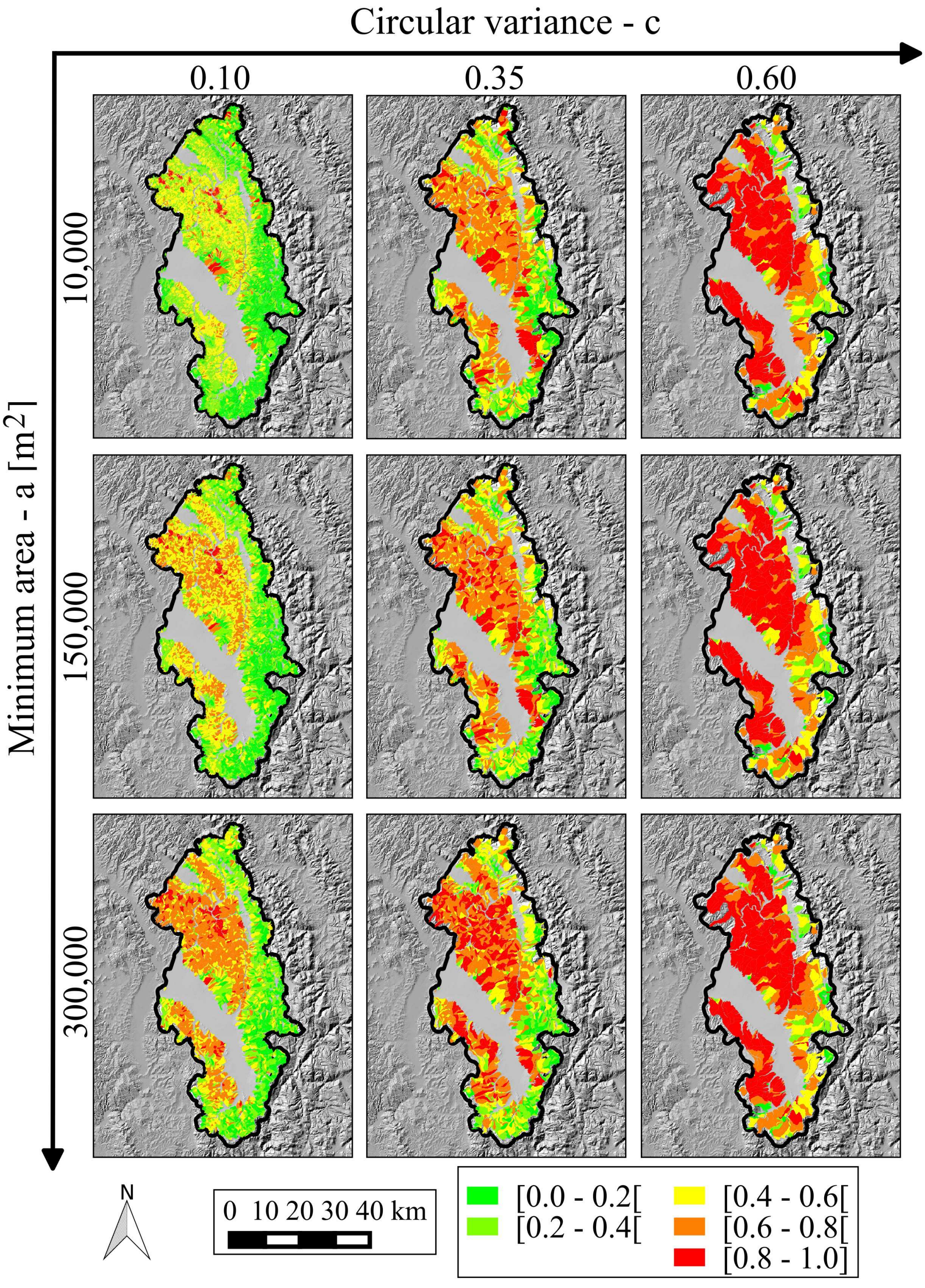

Figure 10. Nine (out of 99) landslide susceptibility (LS) maps obtained with different slope-units (SU) partitions resulting from different combinations of the a and c parameters. The maps are in the UTM zone 32, datum ED50 (EPSG:23032) reference system.

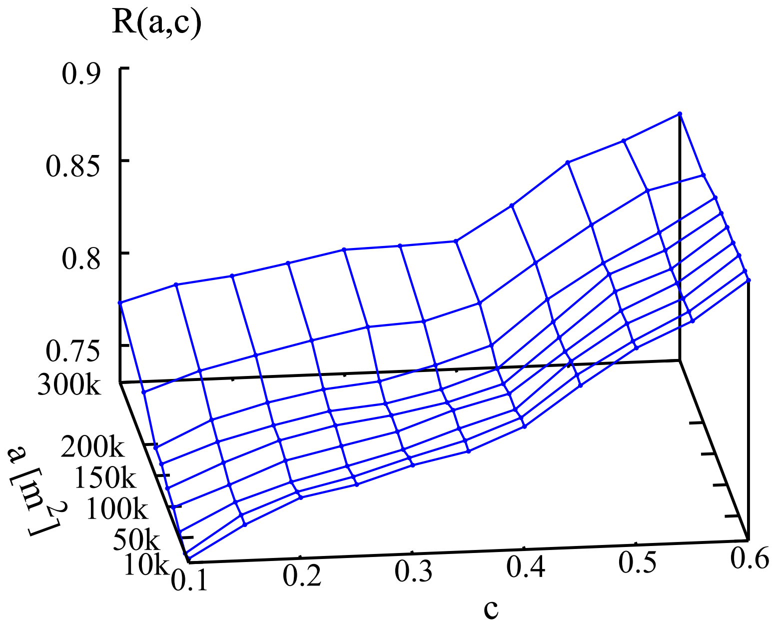

Figure 11. Values of the Area Under the ROC Curve (AUC_{ROC}) calculated for landslide susceptibility (LS) maps estimated using slope-units (SU) partitions derived for different combination of the a and c user-defined modelling parameters.

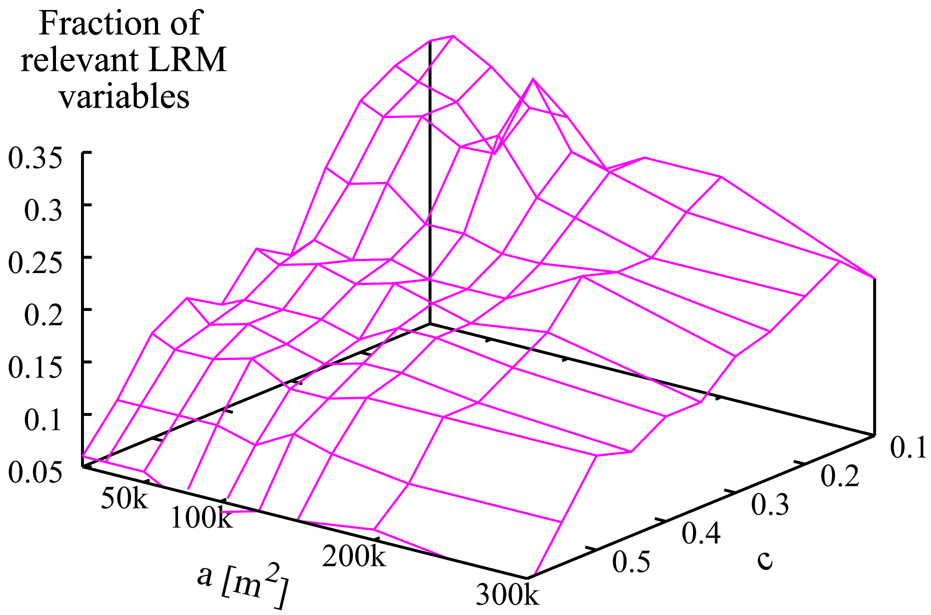

Figure 12. Percentage of relevant variables in the Logistic Regression Model (LRM) used in this work to prepare the landslide susceptibility (LS) maps as a function of the a and c user-defined modelling parameters. Combination of a and c are the same used to prepare Fig. 11. Note that the direction of the axes are reversed with respect to Fig. 11.

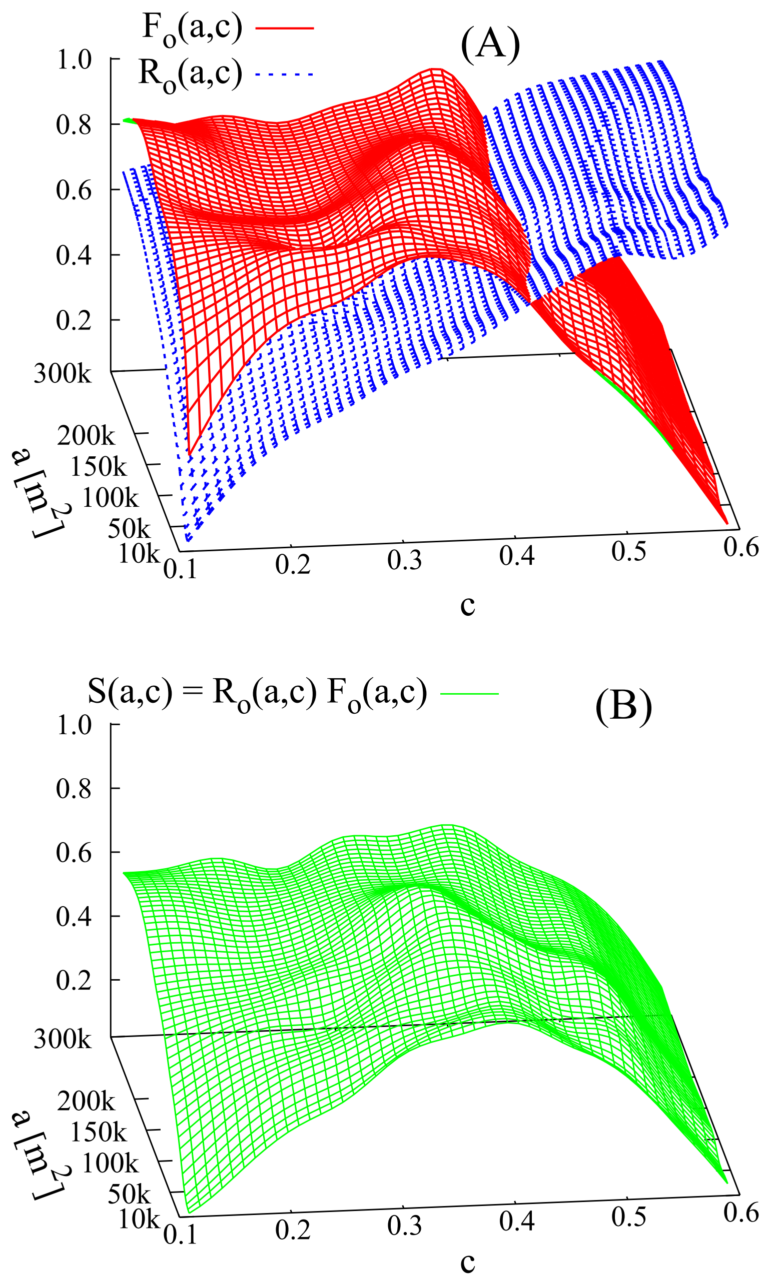

Figure 13. (A) $R_o(a, c)$ (blue) and $F_o(a, c)$ (red) functions, defined by Eqs. (9), (10). (B) $S_o(a, c)$ function defined by Eq. (11). The functions were interpolated on a denser mesh for improved visual representation.

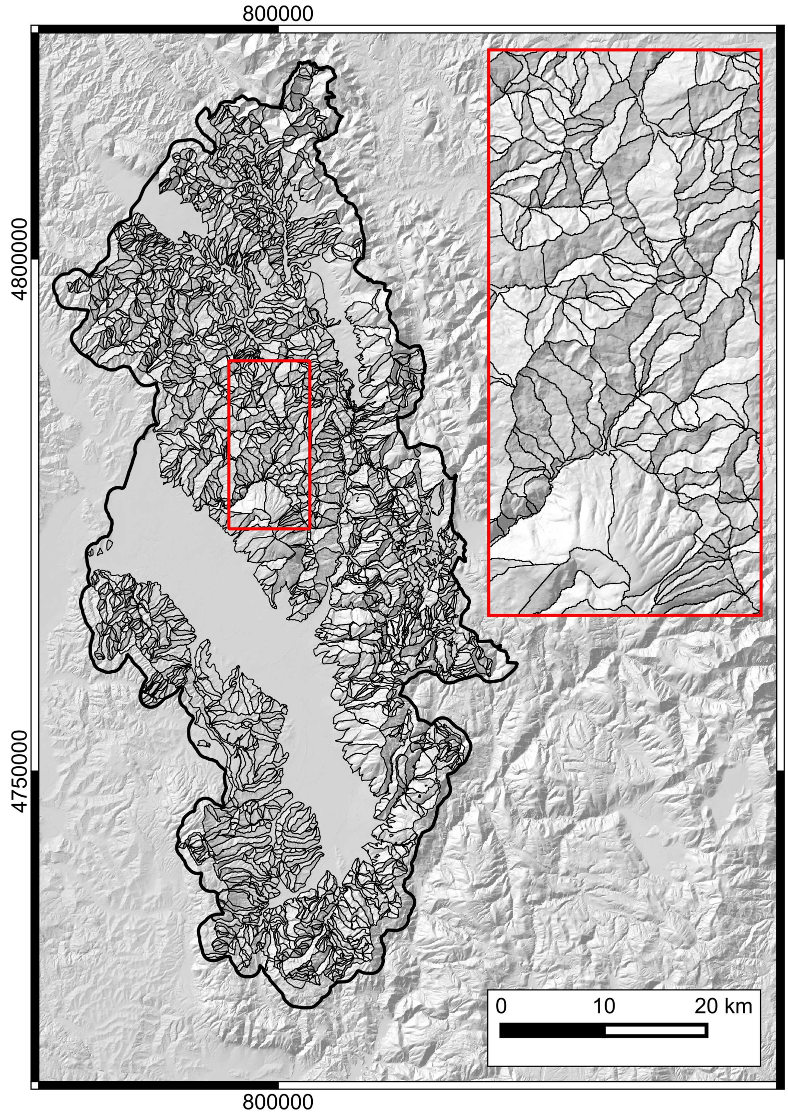

Figure 14. The SU subdivision corresponding to the "best" parameters, selected by our otpimization procedure. The values of the parameters are: a = 150,000 m^2, a = 0.35. The associated LS result is shown in Fig. 10, in the central box, corresponding to the optimal parameters values.