Answer Reviewer 3

General comments

The manuscript under review presents a well-conceptualized and executed study that aims to analyze how different approaches to defining source areas can influence the accuracy of rockfall modelling, using a methodological experiment conducted on the island of El Hierro (Canary Islands, Spain). Although the topic of rockfall susceptibility modelling is common in the literature, this study makes an interesting contribution by highlighting the critical importance of source area definitions. The experiments conducted strongly support the prioritization of probabilistic approaches for identifying source areas at a regional scale, and the manuscript argues effectively for the benefits of supervised classification in susceptibility mapping over unsupervised methods. The study is not only of scientific interest but also holds practical value for local managers and stakeholders. The manuscript is generally well-structured and, for the most part, easy to follow. However, the methodological section requires clearer explanations and the inclusion of some missing details, which will be addressed in the specific comments. Overall, I believe that this manuscript has the potential for publication once these comments and corrections have been addressed.

Thank you very much for your positive feedback on the manuscript. We appreciate the important suggestions that will improve the readability and comprehension of the article. In the revised version, we have carefully considered all the comments and suggestions. In the following pages, we present comprehensive responses to each point.

We hope that our replies could be successfully aligned with the request of the reviewer and with the standard of the journal.

Specific comments

In the introduction, the authors talk several times about deterministic, statistical and probabilistic approaches. I suggest to add a few lines explaining the basic differences between these three methodologies in order to ensure that the reader understands correctly what they are trying to explain when they use such a term.

We have added information on the different approaches

Deterministic methods identify rockfall source or detachment locations using models based on mechanical principles, while statistical methods are based on the analyses of historical catalogues of past rockfall events. For the probabilistic identification of source areas, supervised multivariate classification or machine learning models are employed to predict rockfall detachment locations (i.e., dependent or grouping variable) based on a set of explanatory variables (i.e., independent variables).

In section 2.1 the authors offer a good overview of the geographical and geological settings of the study area. However, there is no reference to Figure 1, where the reader can actually locate the many locations mentioned in the paragraph.

We have added a reference in Section 2.1 of Figure 1.

In section 2.2 the authors list some sources of information used to define rockfall source areas, among which there is something cited as "some geomorphological information". I find this phrase too ambiguous and it should be more specific. What exactly did they use?

Many thanks we have added this text:

We have modified the text in the first paragraph of the section 2.2 to explain which information we have used, namely landform features derived from DEM analysis with Geomorphons approach (Rossi et al., 2020).

In section 2.2 there is the weak point of the paper. If I have well understood, some crucial steps of the analysis are dependent on the available rockfall inventory. For instance, the ECDF model is built on data obtained within the mapped source areas; so is for the training and validation of the probabilistic model (logistic regression); and the supervised classification approach is fed by the rockfall deposition zones previously mapped. Notwithstanding, the only information provided about such an inventory is that they are "areas affected by rockfalls where we have identified detached boulders by field investigation". It is not clear if source areas and deposition areas are independent polygons or not. There is no extra information about the number of the mapped rockfalls and the period in which the field survey was carried out. Furthermore, later in section 3.4 the authors mention two different inventories, but there is no information about what the origin of these data is. In my opinion this is one thing to be improved in the revised version.

We have modified as follow, section 2.2 and Figure 1 to explain better the information available for the area that was used to identify the source areas, train and validate the runout and susceptibility modelling.

In this paper, we have used different thematic data to identify source areas and to perform rockfall modelling and susceptibility zonation. The different methods proposed to identify source areas require diverse type of information: (i) unsupervised STRSA and CDFRSA require only slope data; (ii) supervised STRSA and CDFRSA require slope data and the location of source areas (i.e., normally mapped in the field; see Rossi et al., 2020 for details); (iii) PROBRSA needs also additional geo-environmental information (see Rossi et al., 2020 for details). For the island the following data are available: (1) Digital Elevation Model (DEM) at 5 m x 5m resolution (LiDAR-PNOA Centro de Descargas del CNIG (IGN)) that was used to compute the morphometric parameters (e.g., elevation, slope, curvature, landform classification, etc.); and (2) lithological information derived from the geological map provided by IGME-CSIC at a scale of 1:25000. The map was reclassified into 5 geotechnical classes (Sarro et al., 2020; Rossi et al., 2020), ranging from class 1, which includes soft soils (such as lapilli and sand), to class 5, which includes very hard rocks (dikes, volcanic breccias, and massive basalts).

In addition, for the runout modelling the following additional data were exploited: (i) a sample of mapped rockfall deposits in polygon format for the supervised CDF analyses of rockfall trajectories (Figure 5); (ii) a sample of areas affected or with no evidence of rockfall for ROC-based model performance evaluation (Figure 9); and (iii) a sample of the rockfall boulders location (i.e., silent witnesses) for violin and boxplots susceptibility analysis (Figure 10).

Figure 1 illustrates the distribution of rockfall information used in the runout simulations classification and validation: (1) red polygons show areas affected by rockfalls, where we have identified detached boulders through field investigations conducted from 2012 to 2018 (46 records), aerial images (84 records), and the MOVES database (BDMoves) (78 records), including point features converted into polygons by applying a 50-meter buffer to account for uncertainty in data location; (2) green polygons show areas with no evidence of rockfall activity, mapped in the field by experts with the support of geomorphological and topographical maps; (3) blue polygons show the subset of rockfall deposits (i.e., talus) used in CDF analysis; and (4) black dots show the subset of boulders location used in violin and boxplot analyses.

In section 3 the authors make reference to Figure 2 a couple of times. I'll leave the decision to the authors, but from my point of view it is strange to mention the main results in the methodology section.

We have deleted Figure 2 in some places to clarify the section.

In section 3.1.1 the authors argue some slope angle cut values used in the literature as a threshold, but they do not specify which is the one applied in their study. This is only clarified in section 4.1 (i.e. slope threshold = 40º). This should be clearly specified in the methodology.

The following text has been added:

Considering that the geological context of El Hierro where rockfall occurrences are observed, is similar to Gran Canaria we have defined the threshold above 40°.

In section 3.1.3 there are some confusing explanations. It is not clear if the probabilistic model has been done merging the three outputs of the logistic regression, discriminant analysis and quadratic analysis; or instead, the authors just selected the better performing among them. Another important information is missing: the training and validation sample proportions. For the sake of the comprehensiveness of the paper I suggest to improve this section and to provide more details.

The following text has been modified/added in section 3.1.3:

The final source area zonation was prepared applying a combination of different statistical modelling methods, namely a linear discriminant analysis, a quadratic discriminant analysis, and a logistic regression model. See Rossi et al. (2022) for the details on training/validation/combination procedure.

In section 3.2 the authors mention the need of three coefficient maps in order to run STONE, and that the values of such "coefficients were estimated considering different lithological/geotechnical categories reported in the geotechnical map of El Hierro and selecting values reported for similar lithologies in the literature (Alvioli et al., 2021; Guzzetti et al., 2003; Mateos et al., 2016; Sarro et al., 2020)". Further than that, I find compulsory to specify the coefficient values applied in the study, in order to facilitate the reproducibility of the experiment.

The following table has been added:

USDA Classification	Tangential restitution	Normal restitution	Rolling friction
Extremely hard rock	89	64	0.35
Very hard rock	88	63	0.48
Hard rock	87	57	0.50
Moderately rock	78	46	0.55
Moderately soft rock	75	45	0.59
Soft rock	54	41	0.67
Soils	50	38	0.70

Figure 2. Values of the coefficients used in rockfall modelling considering geotechnical classification.

In section 3.4 the authors introduce two validation tests that are not so common in landslide susceptibility evaluation tests: (i) 2D hexagonal bin count heat maps and (ii) distribution of average susceptibility values within circular buffers (i.e., violin plots). I appreciate the effort made by the authors to include innovative validation proves. However, I believe that some extra explanations in the methodology section about how one should interpret this kind of plots, together with additional references, would improve substantially the quality of the manuscript.

We have used 2D hexagonal bin for maps comparison. We clarify this in the manuscript adding the following text in section 3.3:

Hexagonal binning for map comparison is a technique used in data visualization, particularly when dealing with large datasets in two-dimensional scatter plots. It groups data points into hexagonal "bins" (rather than traditional square bins) to provide a more structured view of the data's distribution. The hexagonal shape is often preferred because it avoids the visual artifacts that can result from aligning data into rectangular grids and provides a more compact and efficient way of packing data points (Wickham, 2016). As suggested by the reviewer, the violin plots are uses as an additional model evaluation. To clarify, we added the following text:

In section 3.4:

Different buffer sizes allow to consider uncertainty due to local conditions and boulders locations. In the proposed approach the location of mapped boulders is used to evaluate the rockfall susceptibility zonation. Commonly this information is mainly used to evaluate runout models verifying if simulations reach entirely or partially the boulder locations. Violin The violin plots show distribution of the susceptibility data and specifically their probability density and together with box plots help visualizing summary data statistics, such as median values and interquartile ranges.

In section 4.2 at the end 4th paragraph:

These plots are divided into hexagonal bins, and each bin is colored based on the count of susceptibility maps value. Dark reddish shades indicate a higher frequency of measurements within the corresponding hexagon, while lighter areas may indicate sparse values.

In section 4.1 I was expecting the validation results of the probabilistic approach applied to generate the PROBRSA map, since in section 3.1.3 the authors state that "Specifically, contingency matrices and plots along with model sensitivity, specificity, Cohen's kappa indices and ROC curves with the corresponding area under curve (AUCROC) values, were used to compare the observed and modelled source areas and to explore quantitatively the performances of different model configurations allowing the selection of the best model and the corresponding probabilistic source area map". In my opinion these are very relevant results that need to be shown up.

In the article "Probabilistic Identification of Rockfall Source Areas at Regional Scale in El Hierro (Canary Islands, Spain)" by Rossi et al. (2020), all the methodologies and results to generate probabilistic RSA are explained in detail, including contingency matrices and plots along with model sensitivity, specificity, Cohen's kappa indices, and ROC curves with the corresponding area under the curve (AUCROC) values. We have chosen to not repeat such information in this article that illustrates several methodologies to derive rockfall susceptibility zonation. We have indicated more clearly in 3.4 the reference where is possible to search such information. We additionally provided a summary in section 3.1.3 and a reference the previous one for further information on the probabilistic source area map.

I strongly suggest improving the writing of Section 4.2. The argumentation was difficult to follow. Since this section discusses the core results, it is important to present it as clearly as possible. Therefore, I recommend dedicating additional effort to ensure clarity in this crucial part of the manuscript.

Many thanks for your suggestion. Section 4.2 have been improved to facilitate understanding:

The output of runout simulation obtained by STONE (Figure 2 d, e, f), using as input the different source areas maps (i.e., STRSA, CDFRSA and PROBRSA), shows diverse spatial distributions of rockfall *trajectory counts providing a potential different information on the susceptibility posed by rockfall in the study area. To facilitate the comparison of rockfall simulations, we proposed classifying the trajectory count maps using two approaches: unsupervised and supervised ECDF analysis (Figure 4 and Figure 5) , to obtain a comparable probabilistic susceptibility map. The application of the ECDFs (i.e., derived for different runout models taking in input different source area maps) to the relative trajectories' count maps, allows to derive the six probabilistic susceptibility maps shown in Figure 4. This figure shows larger differences between the 3 maps for the different source area using the unsupervised ECDFs (Figure 4 a, b, c); such differences are reduced/minor when considering the supervised alternatives (Figure 4 d, e, f).*

For comparison of the six results, different plot representations have been used to facilitate the understanding of this behavior.

Figure 5 shows the unsupervised and supervised ECDF functions derived from the outputs obtained using different source area identification methods. The unsupervised distributions show larger ranges and higher number of cells with low trajectories counts (i.e., values close to 0). Additionally, the comparison of the unsupervised ECDFs (Figure 5 a, b, c) reveals a larger number of cells with high count values for STRSA, followed by CDFRSA and PROBRSA. With this behaviour reversed when considering supervised ECDFs (Figure 5 d, e, f).

Figure 6 and Figure 7 show the pairwise difference of susceptibility maps obtained using different source area maps and diversified classification method. Specifically, the figure portraits the following six pairs of results: (a) STRSA-unsup-CDFRSA-unsup, (b) STRSA-unsup-PROBRSA-unsup, (c) CDFRSA-unsup-PROBRSA-unsup, (d) STRSA-sup-CDFRSA-sup, (e) STRSA-sup-PROBRSA-sup, and (f) CDFRSA-sup-PROBRSA-sup. The lighter colours (i.e., lower absolute difference values) between supervised maps pairs and the frequency counts of the corresponding histograms, highlight lower differences between the susceptibility outputs obtained applying supervised ECDFs.

The 2D hexagonal bin count heat maps (Figure 8), derived for the different pairs of susceptibility maps, confirm these results showing a better alignment along the bisector of the higher frequency counts (i.e., dark reddish hexagons) obtained for supervised susceptibility maps (Figure 4 d, e, f). These plots are divided into hexagonal bins, and each bin is colored based on the count of susceptibility maps value. Dark reddish shades indicate a higher frequency of measurements within the corresponding hexagon, while lighter areas may indicate sparse values.

Furthermore, an analysis has been conducted not only on the variations in the number of trajectories per cell but also on the lithological types through which these trajectories pass. The comparison of the trajectory maps with the simplified geotechnical classes map (Figure 1 in (Rossi et al., 2020)) reveals that the rockfall trajectories mainly involve lithology types classified as very hard rocks and hard rocks, whereas trajectories through soft rocks are quite limited.

Section 5 correctly synthesizes the presented results and draws conclusions that are well supported by the evidence. However, to enhance this section, I would appreciate a more in-depth discussion on the implications of the findings. For instance, does this mean that every rockfall susceptibility analysis should utilize the PROBRSA approach for identifying source areas, in combination with STONE and the ECDF classification method? Additionally, while STONE, like many other rockfall simulation software mentioned by the authors, is effective, it does not account for certain relevant factors in fall trajectories, such as the initial size of the detached boulder or other complex mechanical aspects. A brief discussion of the limitations and advantages of this tool would be valuable for readers to consider.

The authors welcome your suggestion for a more comprehensive discussion on the implications of the findings. We have added the following text:

In the analysis of rockfall susceptibility at a regional scale, access to comprehensive data is frequently limited. This constraint impacts the methodologies employed to definition source areas, which are subsequently integrated as input into modelling software. When only a digital elevation model (DEM) and bibliographic resources are available, deterministic methods are typically the predominant approach. However, in scenarios where additional data, such as geological or geomorphological information, are available, investing time in the cartographic of source areas enables the application of probabilistic methods that yield more robust results.

Furthermore, upon obtaining modelling results—primarily trajectory counts—most studies tend to consider these outputs as definitive. Nevertheless, regardless of the inputs use to obtain these results, implementing a supervised analysis based on inventory data and runout delineation can significantly enhance the precision of the outcomes.

Despite the availability of various software and methods for rockfall runout simulation in the literature, we have selected STONE due to its previous validation and application in the study area. Nonetheless, we recognize that the susceptibility zonation methodology proposed in this study remains relevant even when employing other rockfall modelling software. The tools introduced herein are transferable to other software, as the main difference between the approach to define the source areas, while other input parameters are kept constant. The classification of trajectory counts maps using two methodologies—unsupervised and supervised ECDF analysis—is applicable to the results generated by any software, thereby facilitating the development of probabilistic susceptibility zonation.

Technical corrections (a compact listing of purely technical corrections)

Page 1 – Line 17: "A morphometric firstly approach establishes a slope angle …" Please verify if the sentence is grammatically correct.

We have corrected the sentence.

Page 2 – Line 48: "Rockfalls simulation models …" Shouldn't be Rockfall (singular)? Pease verify.

Done

Page 2 – Line 49: "sources areas…" Shouldn't be source areas? Pease verify.

Done

Page 2 – Line 59: "dataset …" datasets (plural)?

Done

Page 4 – Line 94: "The Canary Islands is a volcanic archipelago …" is or are? Pease verify.

Done

Page 4 – Line 119: you use both modeling and modelling. Please chose one forms and be consistent.

Done

Page 5 – Line 130: "(BDMoves) …" Is it a citation? In such case, the reference is missing in the list. If not, please provide some more info about that because it is not a convention.

Many thanks, yes is a citation. We have added BDMoves: http://info.igme.es/BD2DMoves/) in the list.

Page 6 – Line 158: “For the first statistical identification …” I don’t understand why it is THE FIRST

We have corrected the sentence. “*For the second identification of rockfall source areas, we utilized the Empirical Cumulative Distribution Functions (ECDF) of slope angle values (hereafter referred as CDFRSA).*”

Page 6 – Line 164: “…denotes the CDF of a random…” Do you mean ECDF?

Yes, we appreciate the reviewer’s insight. We have corrected the error.

Page 6 – Line 173 & 176: CDFRSA or ECDFRSA?

In this case, we refer to CDF_{RSA}, which is the term we will use to indicate the source areas obtained with the ECDF.

Page 6 – Line 182: “The model uses in input morphometric …” Remove in.

Done

Page 7 – Line 203: “…employing in input…” as input? Please verify

Done

Page 7 – Line 203: “…the three source areas maps…” source area maps?

Done.

Page 8 – Line 230: “The resulting map is probabilistic with values ranging from 0 to 1 and shows a probabilistic estimation…” too much probabilistic.

We have changed the sentence: “The resulting map displays values ranging from 0 to 1 and shows a probabilistic estimation of the likelihood of a given pixel being affected by a rockfall.”

Page 8 – Line 230: “…three source areas maps…” source area maps.

Done

Page 8 – Line 230: “…ECDFs graphs…” ECDF graphs.

Done

Page 9 – Line 277: The first two sentences are redundant with the previous paragraph. Better to remove.

We agree with the reviewer, and we have deleted the first two sentences.

Page 10 – Line 283: “Furthermore, Table 2 shows…” Its Table 1 I guess.

It is correct

Page 10 – Line 286: “proposed by (Rossi et al., 2020)) and classifies…” Correct citation

Corrected. “*…classes proposed by Rossi et al., (2020)…*”

Page 10 – Line 290: “The output of run-out simulation…” runout.

Done

Page 10 – Line 295: "(Figure 1 in (Rossi et al., 2020)) reveals" (Figure 1 in Rossi et al. (2020)) revealed that the rockfall trajectories

Done

Page 10 – Line 301: the "hard soil" class … quotation marks show different format. Revise in the complete manuscript.

Done, we have deleted all the quotations.

Page 11 – Line 327 & 328: "…the model with the best performance is obtained by using the PROBRSA source areas (AUCROC=0.88), followed by the CDFRSA (AUCROC=0.84)…" You should add the AUROC value of STRSA to this paragraph.

We have added this information.

The graphs show that the model with the best performance is obtained by using the $PROB_{RSA}$ source areas (AUC_{ROC}=0.88), followed by the CDF_{RSA} (AUC_{ROC}=0.84), with ST_{RSA} performing the worst (AUC_{ROC}=0.78).

Page 11 – Line 341: "…source areas of increasingly complexity…" of increasing complexity?

Done.