Reviewer 2

I am rejecting this paper. The study does not present any fundamentally new methodologies for rockfall hazard assessment. It relies on established techniques and applies them in a comprehensive manner. So, no significant contribution to method development other than comparison.

The motivation of the author is not clear. The paper discusses the socio-economic impacts of rockfalls, suggesting that even remote areas can have significant implications, potentially affecting future development, tourism, or local infrastructure. This analysis identifies the sources of rockfall in remote mountainous areas, where there are no populations or roads. As a result, there is no classification of which areas are vulnerable to rockfalls or how these rockfalls might affect populations and development. Identifying rockfall sources in inhabited areas or near infrastructure would be beneficial for safety and planning purposes. However, the necessity of finding rockfall sources in remote areas without development is not clearly explained, leaving the practical relevance of this study in such locations unclear.

While the paper overviews the data used for identifying rockfall source areas and modelling susceptibility, it lacks details on data acquisition and processing. Although a 5m x 5m DEM from IGN is used, the source whether satellite, LiDAR, or other is unclear. Lithological and geological data from IGME-CSIC maps lack detailed classification methods, and geomorphological data are mentioned without specifics on acquisition or use. Historical rockfall events and field observations are referenced for validation, but collection and validation methods are not detailed. The author could add more information.

The paper does not seem to employ a conditional probability framework that explicitly models how a rockfall event influences the probability of subsequent events.

One limitation of the paper is that it does not thoroughly describe the relevance of rockfall trajectories.

Although the study compares different methods, it does not provide a detailed evaluation of why specific factors or combinations of factors lead to better performance.

The paper discusses the results of the different methods used for rockfall susceptibility assessment, identifying which method provides the best results. However, it does not delve into the reasons behind why one method outperforms the others. This lack of analysis of the factors contributing to the best results limits the understanding of the strengths and weaknesses of each approach. Without a clear explanation of why a particular method is more effective, it is difficult to apply these findings in other contexts or to make informed decisions about method selection in future studies.

The slope thresholding approach does not consider other important factors like vegetation or soil type, which can also affect rockfall susceptibility. Although the choice of slope threshold is informed by previous studies and local conditions, focusing primarily on slope and lithology, it can still be somewhat arbitrary. Without proper validation, this method may not accurately identify all rockfall-prone areas, potentially leading to inaccuracies. The methods and findings are specific to the geological and topographical context of El Hierro, a volcanic island, and do not offer clear guidance on adapting these methods to other regions, limiting their generalizability.

Thank you very much for your comments and feedback on the manuscript. We would like to clarify some points that, in our opinion, do not reflect the content and the main objectives of the manuscript or that are addressed in the text may be not clear enough to be understood by the reader.

We would like to clarify, highlight, and address each point of the reviewer to provide some more clear explanation of our work.

Answers Reviewer 2

The motivation of the author is not clear. The paper discusses the socio-economic impacts of rockfalls, suggesting that even remote areas can have significant implications, potentially affecting future development, tourism, or local infrastructure. This analysis identifies the sources of rockfall in remote mountainous areas, where there are no populations or roads. As a result, there is no classification of which areas are vulnerable to rockfalls or how these rockfalls might affect populations and development. Identifying rockfall sources in inhabited areas or near infrastructure would be beneficial for safety and planning purposes. However, the necessity of finding rockfall sources in remote areas without development is not clearly explained, leaving the practical relevance of this study in such locations unclear.

The main focus of the article is not the discussion of "*the socio-economic impacts of rockfalls.*" but it presents a workflow that analyses how different source areas delimitation influences the rockfall modelling results. In particular, three types of approaches are considered for defining source areas, depending on data availability scenarios. Different source area maps are used as input data to rockfall runout model, which outputs are classified to derive rockfall susceptibility zonation.

The word "*socio-economic*" appears only in the abstract to justify the selection of El Hierro as the case study, and in the introduction to mention that "*rockfalls are dangerous natural hazards with a relevant socio-economic impact worldwide (Borella et al., 2019; Mateos et al., 2020).*"

The sentence "*This analysis identifies the sources of rockfall in remote mountainous areas, where there are no populations or roads*" does not accurately represent the scenario in El Hierro. The island has approximately 11.646 inhabitants, and the floating population may significantly increase due to the high demand for rural and natural tourism, as indicated by the extensive network of tourist trails and public-use infrastructure available throughout the island.

In addition, the objective of this article is not to estimate vulnerability. And this is the reason why "*there is no classification of which areas are vulnerable to rockfalls*" We appreciate the reviewer's suggestion, as it could provide a valuable direction for future research.

In addition, we would like to underline that the manuscript presents a workflow from rockfall source areas identification to susceptibility zonation at a regional scale. Vulnerability, risk assessment and the impact of rockfall on structures and infrastructures is not part of the topics discussed in the article.

Although a 5m x 5m DEM from IGN is used, the source whether satellite, LiDAR, or other is unclear. Lithological and geological data from IGME-CSIC maps lack detailed classification methods, and geomorphological data are mentioned without specifics on acquisition or use. Historical rockfall events and field observations are referenced for validation, but collection and validation methods are not detailed. The author could add more information.

To clarify these points, chapter 2.2 "Available data and products" was completely rephrased

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.

The paper does not seem to employ a conditional probability framework that explicitly models how a rockfall event influences the probability of subsequent events.

The authors acknowledge the importance of this point, as a rockfall event can significantly alter the conditions of the slope, affecting the probability of future rockfalls.

However, the presented work does not fully capture the dynamics of these phenomena in complex scenarios where events may be interrelated. While the scenario you present is indeed interesting, it falls outside the scope of this study.

One limitation of the paper is that it does not thoroughly describe the relevance of rockfall trajectories.

This topic is widely discussed in the literature, but this paper focuses on the entire workflow leading to the estimation of the susceptibility posed by rockfalls starting from the identification of source areas applying different methods to the classification of trajectory count maps and the evaluation of the final susceptibility zonation.

Although the study compares different methods, it does not provide a detailed evaluation of why specific factors or combinations of factors lead to better performance.

It's not clear if the terms "specific factors" refer to environmental factors that are considered in the modelling or to the different steps of the proposed workflow.

The paper discusses the results of the different methods used for rockfall susceptibility assessment, identifying which method provides the best results. However, it does not delve into the reasons behind why one method outperforms the others. This lack of analysis of the factors contributing to the best results limits the understanding of the strengths and weaknesses of each approach.

Without a clear explanation of why a particular method is more effective, it is difficult to apply these findings in other contexts or to make informed decisions about method selection in future studies.

In section 3.3, we describe two possible classification approaches for the rockfall trajectory counts, based on (i) an unsupervised and (ii) a supervised statistical approach exploiting Empirical Cumulative Distribution Functions (ECDF). The unsupervised classification requires, as input, the raster map of rockfall trajectory counts. This map is then classified using the ECDF function derived by accounting for all count values greater than or equal to 1. To perform the supervised classification of the rockfall trajectory count map, additional information on observed (i.e., mapped) rockfall deposits is needed. In this case, the ECDF function was derived by considering only the count values of the pixels within the rockfall deposit polygons. The output map provides a different probabilistic estimate of a given pixel being affected by a rockfall and can be interpreted as a susceptibility map. In the same chapter we describe the different analyses we have used to compare the final classified susceptibility maps.

The slope thresholding approach does not consider other important factors like vegetation or soil type, which can also affect rockfall susceptibility. Although the choice of slope threshold is informed by previous studies and local conditions, focusing primarily on slope and lithology, it can still be somewhat arbitrary. Without proper validation, this method may not accurately identify all rockfall-prone areas, potentially leading to inaccuracies.

The existing literature on rockfall, including an article we have published for Gran Canaria (Canary Islands), indicates that the value selected for El Hierro is consistent with the range commonly selected by the scientific community. It's very difficult to consider the influence of vegetation in slope thresholds analysis because this information is often missing or not complete for areas with a big extension.

We added the following information:

Sarro et al. (2020) proposed a slope threshold over 40º in Gran Canaria (Canary Islands), an island with similar topographical and geological conditions than El Hierro. Detailed evaluations revealed that the source areas in Gran Canaria are primarily associated with hard, very hard, and extremely hard rocks, corresponding to geological types such as dykes and breccia, phonolite, massive basalt, trachyte, and ignimbrite.

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°.

The methods and findings are specific to the geological and topographical context of El Hierro, a volcanic island, and do not offer clear guidance on adapting these methods to other regions, limiting their generalizability.

We appreciate the comment, but we do not agree with this statement.

The workflow is designed to be reproducible in various geological contexts. The tools developed for this work are applicable across diverse geological settings. For instance, the identification of source areas, whether through slope thresholds or ECDF, can be effectively conducted in any context. While the probabilistic approach does account for factors specific to volcanic areas, such as dikes, the tool utilized (LANDSUITE) can be employed in a wide range of contexts by considering the primary factors that determine rockfalls.

In the case of deterministic rockfall runout simulation, the STONE software has been successfully applied in numerous geological contexts, and the literature supports this application. Furthermore, in generating a probabilistic susceptibility map through the classification of rockfall runout, we employed two classification approaches based on the ECDF of trajectory counts. This classification is conducted by considering (1) areas affected by rockfalls, where we have identified detached boulders through field investigations, aerial imagery, and the MOVES database (BDMoves); and (2) (green polygons) areas with no evidence of rockfall activity.

Lastly, the tools for representing comparisons on different susceptibility maps can also be utilized in any geological context.

We would like to express our gratitude for your review. We trust that we have adequately addressed your comments and that the new modifications make the article more robust.