

Dear Dr Ben Mirus,

Thank you for your nice and constructive comments. We have addressed your comments point-by-point and provided the answer, explanation, and modification where are required in the revised manuscript. This has been uploaded as a supplement file where you can find our answers in a table plus the revised manuscript with track changes.

We hope our answers satisfy your demands.

Best regards,

Jalal Samia and the co-authors

Referee's comments:

Authors responses :

Comment	Response
<p>General Comment:</p> <p>Given the superior performance of the “path dependent only” model over the “conventional” model, it is important to note that at least the spatial part of the path dependent model may not be entirely related to the occurrence of past landslides. Rather this might also be at least partially explained by the generally accepted phenomenon that landslides tend to happen where they have already occurred previously. That is, there could be factors that are not considered in the conventional model that explain the “where” of landslide occurrence better than the terrain attributes considered. For example, soil thickness or hydromechanical properties or climatic and environmental forcing factors that vary independently of topography. Thus, it is unclear how much the timing of previous landslides is relevant compared to merely the occurrence of past landslides. Perhaps this would be beyond the scope of this study, but it would be very interesting if the authors could somehow separate the spatial and temporal element to see how much of the model improvement is related to “landslides occur here” vs. “a landslide just occurred here” phenomena. This is interesting because it offers the possibility that historic landsliding (without a multi-temporal dataset) could be used as a variable to improve susceptibility modeling instead of trying to account for the difficult to measure subsurface variables. These points are worth mentioning in the discussion section to provide further context for the significance of the contribution and possible future directions.</p>	<p>Thank you for such a nice remark. Indeed this might be that the spatial part of path dependent model is not entirely related to the space-time effect of past landslides but could be partly because those places are unstable slopes where landslides keep occurring. The two landslide path dependency variables implemented in the conventional plus path dependent and purely path dependent landslide susceptibility models were derived simultaneously from Ripley's space-time k function in the line of joint spatial and temporal effect of landslide path dependency on future susceptibility, and are not separable with Ripley's function.</p> <p>In the revised manuscript, we have considered your point in the discussion as following:</p> <p>“The performance of this path dependency-only model thus highlights that proximity to previous landslides can adequately capture susceptible locations. It also suggests that the path dependent models' success in our experiments may be partly due to the fact that they capture static spatial effects that have not been resolved with our explanatory factors. It is attractive to imagine follow-up work that attempts to disentangle this static spatial effect that is unrelated to landslide history from dynamic spatial effects that are related to landslide history. The key to such disentangling should be that the former does not decay over time, whereas the latter does. More advanced statistical approaches that simultaneously estimate purely spatial and spatiotemporal effects may be needed.”</p>
<p>Specific Suggestions:</p> <p>L214. Here and elsewhere I suggest using the Oxford comma to appropriately distinguish between items in a list. It is used sometimes in the manuscript but not consistently.</p>	<p>We took care of this throughout the manuscript in the updated version.</p>
<p>Specific Suggestions:</p> <p>L225. Figure 6. What does the color red/green represent?</p>	<p>The colours represent the intensity of STC measure. We have added two sentences to the caption of figure 6 to make this clear as following:</p> <p>“The colours represent the intensity of STC measure. Red colour indicates high STC and green indicates low STC.”</p>
<p>Specific Suggestions:</p>	<p>Thank you for your observation. Indeed this is not immediately clear on the pie chart of only path</p>

<p>L270. Figure 7. In the Path dependent only case, there is clearly some red (0.8-1.0) on the map, but the pie chart indicates that 0% are in this class?</p>	<p>dependent map. The 0 % belongs to the probability class of 0-0.2 where is not computed in the only path dependent susceptibility map nor. The 0.32% belongs to the red colour in the map. We removed 0% and updated the map in the revised manuscript, and now the number is clear on the pie chart.</p>
<p>Specific Suggestions: L375. There are three models considered, so perhaps edit to: “In both improved models. . .”</p>	<p>Thank you for your suggestion, indeed that works better. We have edited that sentence to your suggested one.</p>
<p>Specific Suggestions: L381-387. It could be worth mentioning that precisely this phenomenon was observed at our site near Seattle (Mirus et al., 2017), namely for the same sequence of storm events a previous landslide remobilized multiple times whereas a neighboring hillslope with the same terrain attributes did not fail.</p>	<p>Indeed an example of observed dynamic susceptibility in your study area could be mentioned in that section of manuscript. We have added this point as following in the updated manuscript: “Such dynamics have been observed in a site near Seattle, Washington, where several new landslides occurred in a slope that had recently experienced landslide activity whereas a nearby hillslope with the same characteristics but without recently landslide activity did not experience new landsliding (Mirus et al., 2017).”</p>

Dear Reviewer,

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Referees' comments:

Author's responses :

Comment	Response
<p data-bbox="203 289 381 317">General remarks</p> <p data-bbox="203 348 799 558">1. It should be noted though that this is the fourth publication of the authors with the same dataset for a small study area. I know that such multi-temporal datasets are scarce, but in order to prove the idea I think it is also important to test the concept with other datasets rather than introducing yet another tweak in the methodology.</p>	<p data-bbox="824 289 1417 436">Thank you for this remark. This is absolutely true, and indeed the concept of landslide path dependency should be explored in other landslides prone areas providing that multi-temporal landslide inventories are available. We have two arguments for this:</p> <p data-bbox="824 474 1417 741">a) As you mentioned, in order to explore the effect of landslide path dependency, the main requirement is the availability of multi-temporal landslide inventory which to the best of our knowledge (at the starting time of this project, start of PhD of the corresponding author in 2013) was rare. We are now aware of a few more multi-temporal inventories (Asturias in Spain and Ubaye Valley in France), that we are going to use then in a follow-up project if the proposal of that is granted.</p> <p data-bbox="824 779 1417 1409">b) The reason for another tweak in the methodology is that in the implementation of landslide path dependency on landslide susceptibility model in the resolution of slope unit (see Samia et.al, 2018), we found that the performance of landslide susceptibility model did not change substantially. We had this reasoning that the effect of landslide path dependency might be captured better in more finer resolution in the mapping unit of landslide susceptibility model due to the local effect of landslide path dependency. The results of this paper confirmed our previous reasoning. Therefore, this justifies our another tweak in the methodology where we converted the polygons of landslides to point, and then used a new metric (Ripley function) to quantify the effect of landslide path dependency. Having said, and considering the substantial importance of landslide path dependency on the performance of landslide susceptibility model, we believe that landslide path dependency is an important component in landslide susceptibility definition, and this should be further explored in other landslide prone areas.</p>
<p data-bbox="203 1507 381 1535">General remarks</p> <p data-bbox="203 1570 799 1780">2. It is also hard for me to follow the interpretation and conclusion that the models considering path dependency are “substantially” better than the conventional one. With the information provided I consider it hard to take a decision at all, but I would tend to rate the conventional model as the best, see also my comments below.</p>	<p data-bbox="824 1507 1417 1858">The conclusion comes from the comparison of performance of three landslide susceptibility models with the metrics of AUC and AIC. This improvement comes from adding only two variables reflecting landslide path dependency to the existing 16 DEM-derivatives. An increase from the AUC of conventional susceptibility model with the value of 0.704 to the AUC value of 0.764 for the conventional plus path dependent susceptibility refers to “substantial” improvement of landslide susceptibility model. Also, AIC values for conventional plus path dependent and purely path dependent landslide susceptibility models are lower</p>

	(11711 and 12469) which are lower than the AIC value of conventional susceptibility model (12678).
<p>General remarks</p> <p>3. I think it is necessary to also show the detailed susceptibility maps of the conventional model to be able to compare the spatial performance. In all path dependent susceptibility maps it is obvious that the path dependent variables clearly dominate the spatial distribution of landslide susceptibility (bullseye artifacts). Are those “hot spot” susceptibility maps useful in practice? Are the models well-balanced?</p>	<p>Regarding the detailed maps of conventional susceptibility see our answers in the comment number 14 in the below.</p> <p>we have considered your comment regarding the applicability of dynamic landslide susceptibility maps in practice as following:</p> <p>“In reality, static susceptibility maps created (either with a conventional susceptibility model, or as the static portion of a conventional plus path dependent model) can be used in sustainable planning whereas dynamic susceptibility maps can be considered in short-term land use planning.”</p> <p>The hotspots in the susceptibility maps of conventional plus path dependent and purely path dependent landslide susceptibility, show the predicted susceptibility per time slice given the history effect of previous landslides. Surely those hotspots are useful in practice in that given period as it reflects that newly happened landslides have higher susceptibility level demonstrating more cares for practical purposes.</p> <p>We are not quite sure what you mean with well-balanced model but our datasets used in the three susceptibility models are balanced.</p>
<p>General remarks</p> <p>4. The conventional model probably has a poor variability as it only contains DEM derived variables. What happens if more fundamental information is introduced, like lithology? I understand that it was intended to use a model with minimal data requirements, but it also hast to be demonstrated first that this works comparing it to a more complex dataset.</p>	<p>Thank you for this point. Aa you also have mentioned, this was our aim to model landslide susceptibility using minimum data requirements (DEM-derivatives) plus variables derived from landslide path dependency. However, we did that work and it’s just not in the paper. The conventional susceptibility modelled by DEM-derivatives, geology and land use has lower model performance (AUC = 0.771) when adding two landslide path dependency variables in the conventional plus path dependent landslide susceptibility (AUC = 0.801).</p> <p>Considering your comment, we also feel that this could be mentioned in the discussion of paper as following:</p> <p>“More complex explanatory variables such as geology, soil and land use can also be used along with DEM-derivatives to improve landslide susceptibility models and maps. However, these are not always available. In fact, considering landslide path dependency effect into such complete explanatory factors improve their performance as well. We confirmed this in an additional</p>

	<p>exploration where we constructed a conventional landslide susceptibility model used in this paper, with the same DEM-derivatives, but also with land use and geology as explanatory factors. The results demonstrated that adding our two landslide path dependency variables to such an improved conventional landslide susceptibility increased its performance (from AUC value of 0.771 to AUC value of 0.801).”</p>
<p>General remarks</p> <p>5. The methodology is also not completely clear to me based on the explanations provided. Were models produced for different time slices or only one model for each parameter set?</p>	<p>Indeed the methodology for modelling part is not completely clear. We have updated the manuscript in this matter (in line 216-220) as following:</p> <p>”Conventional landslide susceptibility was modelled using DEM-derivatives only once for the defined training dataset and was tested using the independent testing dataset. Conventional plus path dependent landslide susceptibility model was constructed using DEM-derivatives plus the two landslide path dependency variables. The purely path dependent landslide susceptibility was modelled only by using the two landslide path dependency variables. All three models were constructed only once.”</p>
<p>Methodology</p> <p>6. E.g. L 94-98: To better understand the whole concept it would be good to understand how the authors define “follow-up landslides” and if/how they are for example discriminated from reactivated landslides.</p>	<p>This comment is confusing since in the lines of 94-98, we did not talk about follow-up landslides at all. However to make it clear, in our previous paper in Samia et al, 2017, we introduced for the first time the term “follow-up landslides” and differentiated that from reactivated landslides as following:</p> <p>“Note that follow-up landslides are not reactivated landslides. We consider a landslide a reactivated landslide when all or most of the landslide moved down again, under the same general condition as the first landslide. Instead, follow-up landslides are new landslides that have different size and shape than the pre-existing landslide.”</p> <p>In the current manuscript when talking about follow-up landslides (mainly in the discussion), the proper reference has been provided.</p>
<p>Methodology</p> <p>7. L 112-113, Fig. 1: Is this figure not taken from Samia et al. 2017a or b?</p>	<p>Yes, it is taken from those papers , and also from our paper in Samia et al, 2018. We have added those two references in the updated manuscript.</p>

<p>Methodology</p> <p>8. L 183, Fig. 5: The figure is not referred to in the text. Is it correct that the arrows on the left point from the start to the results? Are they not supposed to start at the Smoothed STC sketch?</p>	<p>Thank you for this point, indeed the figure is not referred in the text. Now we have provided reference for this figure in the line of 175 where we talk about the computation of the two landslide path dependency variables.</p> <p>Also we appreciate your comment about the position of arrows in Fig. 5. You are right and we corrected the figure in the updated manuscript.</p>
<p>Methodology</p> <p>9. L 205-215: I am not sure if I understand the composition of the training and testing data and the whole procedure. Were the models trained on a single time slice from L 201 each and then tested with the subsequent testing time slice from L 202? Then 10 samples were taken for each time slice? How were the results in tables 1 and 3 generated from the different time slice models? Maybe the methods section could be put more clearly.</p>	<p>No, the model was trained to the combination of time slices 1947, 1954, 1981, 1985, 1999, May 2004, March and May 2010. After that, the model was tested on testing dataset which is the combination of time slices of 1965, 1977, 1991, 1997, December 2004 and 2005 and April 2013 and 2014. Then, due to the unequal amount of pixels with and without landslide in each of these training and testing datasets, we selected 5000 pixels with landslides and 5000 pixels without landslides randomly in each of training and testing dataset. This random selection was repeated 10 times in both training and testing datasets. Therefore, for each of these 10 random datasets, conventional, conventional plus path dependent and purely path dependent landslide susceptibility models were constructed, and the results presented in the table 1 and table 3, are the average of these 10 models.</p> <p>To make this part more clear, we have modified sentences in the lines of 200-203 as following:</p> <p>“To achieve this, all landslides in the time slices of 1947, 1954, 1981, 1985, 1999, May 2004, March and May 2010 were used for training, and all landslides in the time slices of 1965, 1977, 1991, 1997, December 2004 and 2005 and April 2013 and 2014 were used for testing (Figure 1).”</p> <p>Also sentences in the lines of 209-213 were updated as:</p> <p>“Therefore, we randomly selected 5,000 pixels with landslides and 5,000 pixels without landslides from both training and testing datasets in order to create equal datasets both for training and testing of the models. This random selection of pixels was repeated 10 times both in the training and testing datasets. Therefore, we trained the conventional, conventional plus path dependent and purely path dependent landslide susceptibility 10 times, and finally tested 10 times as well.”</p>

<p>Results and discussion</p> <p>10. L 218-219: Is it possible to show a map of what the variables reflecting the path dependency look like spatially?</p>	<p>No that's not possible. We can only make prediction from these variables depending when and where previous landslides happened. We have already shown the examples of the predictions from landslide path dependency variables in our existing figures 8 and 9.</p>
<p>Results and discussion</p> <p>11. L 225, Fig. 6: What does the color code represent?</p>	<p>The colors represent the intensity of STC measure. We have added two sentences to the caption of figure 6 to make this clear as following:</p> <p>“The colours represent the intensity of STC measure. Red colour indicates high STC and green indicates low STC.”</p>
<p>Results and discussion</p> <p>12. L 228-230: Isn't a spatial scale of 60 m quite small? Because 60 m can be below the size of a single landslide. Are these new landslides or reactivated ones?</p>	<p>We noted that the 60 meters is the characteristic spatial scale of the exponential function so that substantial effects still exist over distances more than hundred meters. Moreover, this has been calculated from centre point to the centre point of different landslides and so if the centre points are 60 or 100 or 150 meters away from each other, they could still be not overlapping or overlapping and they could be either new or reactivating landslide. This empirical procedure does not distinguish between new and reactivated landslides.</p>
<p>Results and discussion</p> <p>13. Table 1, Table 3: Are the results available for different time slices? It is unclear to me which results are presented here. Is this a summary of all time slice models? Or the best models?</p>	<p>Considering the explanations given above in the methodology part, the results presented in these two tables should already be clear. However, to make this even more clear, we have modified the caption of table 1 and table 3 as following:</p> <p>“The values of AUC represent the average AUC values in the 10 training and 10 testing datasets. The values of AIC represent the average AIC values in the 10 training datasets.”</p> <p>“Contingency tables computed with cut off value of 0.5 for the three models. The numbers in the table represent the average values computed in the 10 training and 10 testing datasets.”</p>
<p>Results and discussion</p>	<p>We have explained this in above. Just to recall, this conclusion comes from the comparison of AUC and AIC values of these three models and not based on the</p>

<p>14. Section 5.2, Table 3: I do not agree with the interpretation that the conventional plus path dependent and path dependent models are substantially better than the conventional one. The conventional one has slightly more hits and less misses (false negative). In my opinion, false negatives are more critical than false positives, which actually contribute to a better zonation when the goal is not the accurate detection of landslides but the identification of susceptible areas. It would be interesting to see also the susceptibility maps (like figures 8 and 9) for the conventional models to be able to better compare their spatial performance. Success rate curves plotting the distribution of landslides over the susceptibility classes would add more information.</p>	<p>values presented in table 3, which result only from an arbitrary 0.5 cut off value.</p> <p>It's not possible to make conventional susceptibility map like the dynamic path dependent susceptibility maps in figure 8 and 9 because only one conventional landslide susceptibility map was made based on the conventional definition of landslide susceptibility which is a time-invariant concept. The relevant spatial comparison is shown in figure 7 where we show the static susceptibility map from conventional model along with examples from one time slice of the other two path dependent dynamic models.</p> <p>We have provided the success rate curves for three models in 10 training datasets and also for the testing datasets as new figure 7 in the revised manuscript.</p>
<p>Results and discussion</p> <p>15. L 235-237 and L 339-341, using only path dependent variables: I do not understand, why should we want to predict landslides just based on past landslides? Firstly, at this point multi-temporal landslide inventories are rarely available and secondly, this is in my opinion in disagreement with the fundamental paradigm of data-driven landslide susceptibility analysis, which is deducing landslide occurrence from independent variables. Also, the susceptibility maps based on the path dependent variables only have extreme bullseye effect artifacts and I doubt that the maps are in this form useful for practical implementations.</p>	<p>Thank you for this interesting question and comment. Well, we – for the first time – have challenged the conventional definition of landslide susceptibility with introducing the new concept of path dependency indicating the history effect of landslides on future susceptibility (Samia et al, 2017). With this, landslide susceptibility is not a function that considers only the spatial distribution of landslides along with a set of independent environmental factors but path dependency also needs to be taken into account. This effect was found in exploration of a unique and rich multi-temporal landslide inventory in Collazzone, Italy. Landslide path dependency in this study area indicated that susceptibility is not time-invariant but susceptibility changes over time. With this, a new paradigm for landslide susceptibility is emerging called dynamic path dependent susceptibility which requires exploration of the existence of path dependency, characterization and quantification of such effect, and finally its implementation in landslide susceptibility modelling. This modifies the fundamental paradigm of susceptibility in two aspects: first, spatial and temporal effect of landslide path dependency is an “add-on” dependent variable that has to be considered in combination with independent environmental factors. Second, landslide susceptibility is not time-invariant but instead is dynamic and changes over time. In our study area, this effect was obvious, and had a strong effect on the performance of landslide susceptibility models. However, this new paradigm is in its initial stage and has to be explored and studied in other landslide prone</p>

	<p>areas where detailed multi-temporal landslide inventories are available. We are aware that such multi-temporal inventories are rare but given the substantial progresses made already in remote sensing imagery and techniques, and in near future, this will provide room for creation of more multi-temporal landslide inventories where we believe would be main future direction in the field of landslide mapping and documenting.</p>
<p>Results and discussion</p> <p>16. Figures 7, 8 and 9:</p> <ul style="list-style-type: none"> - the maps would be easier to interpret with a hillshade in the background and the outlines of the corresponding training and/or test landslides, which are required to assess the spatial performance of the models. - it is a good idea to show the distribution of the susceptibility classes, but pie charts are not very effective for comparing multiple part-to-whole relationships. They are inconvenient to read and it is hard to perceive the quantitative relationships. Bar or column charts would be more suitable. - why are there blank/white areas in the maps containing path dependent variables? 	<p>Thank you for this point. We have added the hillshade to the backgrounds of landslide susceptibility maps in the revised manuscript. However, it would not be helpful to show the outlines of landslide because there are too many landslides and they completely cover the area.</p> <p>We appreciate the different preference but we feel that pie charts work better for this study.</p> <p>The reason is that the model does not make a prediction for those areas because one of the explanatory factors contains no data in those areas. This factor is topographic position index (TPI) and it has no data in those areas because the slope is zero. The issue only occurs in the conventional plus path dependent model because only that model uses TPI as explanatory factor. It is easy to assign values of zero to TPI in those areas and then calculate the model with that manually changed TPI but we felt that would not be fair. By using TPI and the conventional plus path dependent model with no data we are underestimating model performance because no landslides occurred in any of no data areas and predictions would be zero if we assign zero values to TPI.</p>
<p>Results and discussion</p> <p>17. L 345: I think this should be the map on the left in Figure 7.</p>	<p>Thank you for your sharp observation. This has been corrected in the updated manuscript.</p>
<p>Results and discussion</p> <p>18. L 347-349, usage of landslide susceptibility maps for amount of time of landslide inventory: I think this is hard to generalize and depends on the task, but for sustainable planning of resilient urban areas I would rather counsel time-insensitive susceptibility models based on intrinsic parameters.</p>	<p>We certainly agree with you. The usage of landslide susceptibility maps indeed depends on the goal and task of audience. We also fully agree with you that for sustainable planning the conventional static landslide susceptibility maps are more useful. However, we believe that the dynamic path dependent landslide susceptibility maps would be also useful both in long-term and short-term planning. The dynamic path</p>

	<p>dependent landslide susceptibility maps consist of a static part taking intrinsic factors into account, and a dynamic part taking landslide path dependency into account. As you also have mentioned, the susceptibility maps in the static part are optimal for sustainable planning. However, if it's possible to compute the full dynamic susceptibility maps as in the Collozzone area, then this would be even more practical both for short-term and long-term planning. Another important point is that the only dynamic part of path dependent landslide susceptibility maps would be also in the interest of short-term land use planners and farmers where they would be aware of the areas with different intensity of landslide susceptibility.</p> <p>As we discussed above, we have updated that part of manuscript in the revised version as following:</p> <p>“The usage of conventional static landslide susceptibility maps and dynamic landslide susceptibility maps taking landslide path dependency depends on the goal and task of audience. In reality, static susceptibility maps created (either with a conventional susceptibility model, or as the static portion of a conventional plus path dependent model) can be used in sustainable planning whereas dynamic susceptibility maps can be considered in short-term land use planning.”</p>
<p>19. Figure 10: I do not understand what hypothetical means. Is this graph based on real data or is this just a sketch?</p>	<p>This is just a hypothetical sketch. We have updated this in the revised manuscript as following:</p> <p>“Conceptual model of implication of dynamic path dependent landslide susceptibility model in landslide hazard assessment.”</p>

1 **Dynamic path dependent landslide susceptibility modelling**

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15

16 **Abstract**

17 This contribution tests the added value of including landslide path dependency in statistically-based landslide
18 susceptibility modelling. A conventional pixel-based landslide susceptibility model was compared with a model
19 that includes landslide path dependency, and with a purely path dependent landslide susceptibility model. To
20 quantify path dependency among landslides, we used a Space-Time Clustering (STC) measure derived from
21 Ripley's space-time K function implemented on a point-based multi-temporal landslide inventory from the
22 Collazzone study area in central Italy. We found that the values of STC obey an exponential decay curve with
23 characteristic time scale of 17 years, and characteristic space scale of 60 meters. This exponential space-time decay
24 of the effect of a previous landslide on landslide susceptibility was used as the landslide path dependency
25 component of susceptibility models. We found that the performance of the conventional landslide susceptibility
26 model improved considerably when adding the effect of landslide path dependency. In fact, even the purely path
27 dependent landslide susceptibility model turned out to perform better than the conventional landslide susceptibility
28 model. The conventional plus path dependent and path dependent landslide susceptibility model and their resulted
29 maps are dynamic and change over time unlike conventional landslide susceptibility maps.

30

31 **1. Introduction**

32 Landslide susceptibility modelling calculates the likelihood of landslide occurrence in a certain location (Brabb,
33 1985). The resulting landslide susceptibility maps from landslide susceptibility models indicate where landslides

34 are likely to occur (Guzzetti et al., 2005). These maps are useful in land use planning and insurance, among others.
35 In this context, different methods and techniques have been used for landslide susceptibility modelling.
36 Reichenbach et al. (2018) classified these methods and techniques into five groups: (i) direct geomorphological
37 mapping, (ii) analysis of landslide inventories, (iii) heuristic or index-based approaches, (iv) physically or process-
38 based methods, and (v) statistically-based techniques.

39 Statistically-based landslide susceptibility techniques have been the preferred technique in the modelling of
40 landslide susceptibility (Reichenbach et al., 2018). In statistical landslide susceptibility modelling, empirical
41 quantitative relations are explored between the spatial distribution of landslides and a set of environmental factors
42 (e.g., slope and geology) (Van Westen et al., 2003; Guzzetti et al., 2005). The spatial distribution of historic
43 landslides, documented in landslides inventories, is therefore a crucial input for statistically-based landslide
44 susceptibility modelling (Guzzetti et al., 2012; Van Westen et al., 2008). Direct field mapping, visual interpretation
45 of aerial photographs and other remote sensing images are the main sources for such mapping of landslide
46 inventories (Guzzetti et al., 2012). Landslides in such inventories are stored as points or polygons. Although
47 polygon-based landslide inventories (Ardizzone et al., 2018; Schlögel et al., 2011; Galli et al., 2008) are becoming
48 increasingly available, in many landslide prone regions only less-detailed point-based landslide inventories are
49 collected (Gorum et al., 2011; Sato et al., 2007; Keefer, 2000). Conditioning attributes used in landslide
50 susceptibility modelling are mainly derivatives of digital elevation models (DEMs) along with geological, soil and
51 land use data (Günther et al., 2014; Neuhäuser et al., 2012; Reichenbach et al., 2018). While geology, land use and
52 soil data are not always available in high detail, DEM-derivatives are easily computed and globally available at a
53 range of resolutions. Therefore, the minimum available dataset for landslide susceptibility modelling includes a
54 point-based landslide inventory and a set of DEM-derived conditioning attributes.

55 Traditionally, landslide susceptibility is considered time-invariant: susceptibility of a place to landslide occurrence
56 is constant over time, at least over decadal scales. Recently, we proposed the concept of time-variant landslide
57 susceptibility, where susceptibility changes over time due to the transient effect of previous landslides on future
58 landslide occurrence (Samia et al., 2017b, a). We referred to such a transient effect as “path dependency”, a term
59 adopted from complex system theory where it is used to describe the concept that the history of a system specifies
60 the future behaviour of a system through legacy effects (Phillips, 2006). In our study area in Umbria, central Italy
61 (Figure 1), we identified the existence of path dependency among landslides: earlier landslides locally increased
62 the susceptibility for future landslides for about two decades, during which the susceptibility decays exponentially
63 over time (Samia et al., 2017b). We first implemented the effect of this landslide path dependency in landslide
64 susceptibility modelling at the scale of slope units. Such units divide an area into hydrological units bounded by
65 drainage and divide lines (Carrara et al., 1991; Alvioli et al., 2016). We found that the impact of path dependency
66 on landslide susceptibility models at slope-unit scale was limited (Samia et al., 2018). This limited impact of
67 landslide path dependency on model predictions was probably due to the fact that landslide path dependency
68 affects landslide patterns at spatial scales smaller than slope units, and we hypothesized that differences between
69 models were likely to increase when including path dependency at smaller spatial scales.

70 The objective of this work is thus to consider the effect of landslide path dependency in landslide susceptibility
71 modelling at the resolution of 10×10 m pixels. We hypothesize that including landslide path dependency will
72 improve the performance of landslide susceptibility models. We also explore whether a purely path dependent

73 landslide susceptibility model, i.e. based solely on landslide inventory information, can provide a meaningful
74 landslide susceptibility map. We use the unique multi-temporal landslide inventory from the Collazzone study area
75 (Figure 1) (Guzzetti et al., 2006a; Ardizzone et al., 2007; Ardizzone et al., 2013).

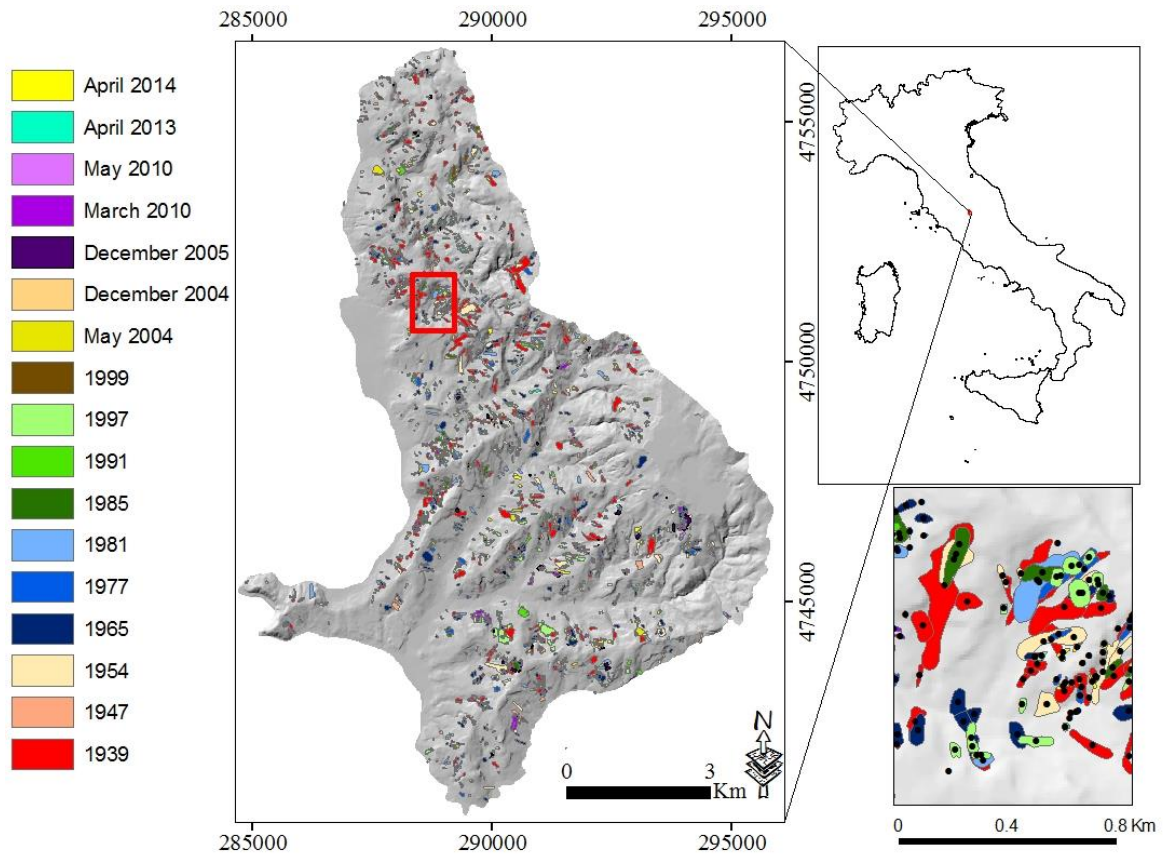
76 **2. Study area and data**

77 The Collazzone study area, Umbria, central Italy (Figure 1), extends for about 80 km² with terrain elevation
78 between 140 to 632 m and terrain slope derived from a 10 × 10 m DEM (Figure 2) between 0 to 64°. The DEM
79 was prepared by interpolating 5- and 10-m contour lines shown in 1:10,000 topographic maps (Guzzetti et al.,
80 2006b). A set of DEM-derivatives that has been widely used in landslide susceptibility modelling was computed
81 in SAGA GIS and ArcGIS. We expect that these DEM-derivatives capture topographical, geomorphological and
82 hydrological properties of locations in our study area.

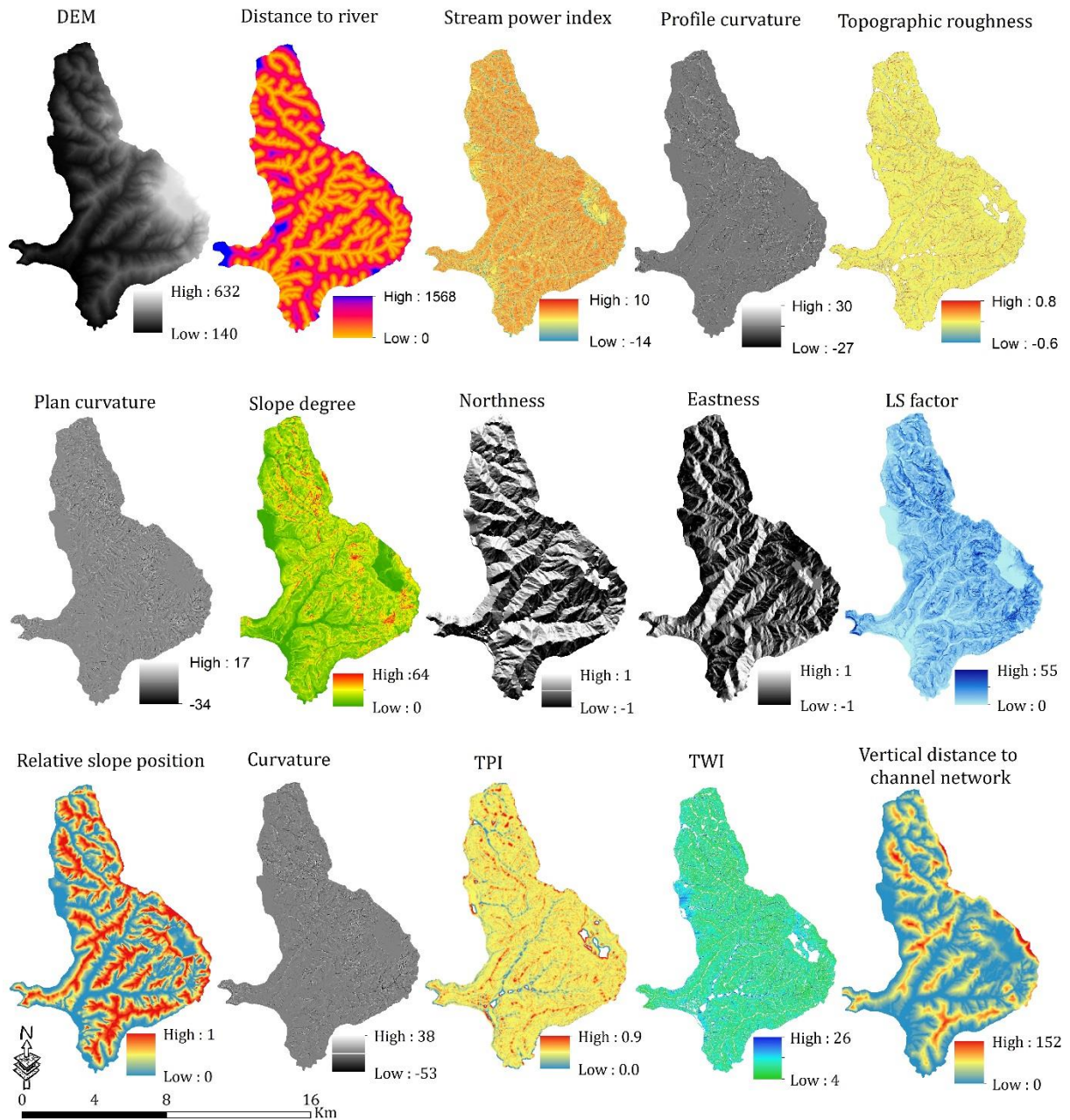
83 The DEM-derivatives (Figure 2) are slope angle, curvature, plan and profile curvature, aspect, northness and
84 eastness as cosine and sine transformations of aspect, topographic position index (TPI) representing different
85 geomorphological settings (Costanzo et al., 2012), stream power index (SPI) representing the erosive power of
86 streams (Moore et al., 1993), topographic wetness index (TWI) as an index for hydrological process in the slope
87 (Jebur et al., 2014). Additionally, for every pixel we computed the distance to the nearest river, the slope length
88 and steepness factor (LS factor) as an index for soil erosion on slope (Moore and Wilson, 1992), the vertical
89 distance to the slope's channel network, and relative slope position representing the relative position of slope in
90 cells between the valley bottom and ridgetop. Additionally, we calculated topographic roughness, which expresses
91 the difference in the values of elevation in the neighbouring cells in the DEM (Riley et al., 1999), and the standard
92 deviation of elevation and slope in a 3 × 3 pixel window. These 16 DEM-derivatives were used as independent
93 explanatory variables in logistic regression for modelling of landslide susceptibility (see section 3.2).

94 Landslides are abundant in this area, and range from recent shallow landslides to old deep-seated landslides
95 (Guzzetti et al., 2006a). Intense and prolonged rainfall and rapid snowmelt are the main triggers of landslides in
96 the area (Cardinali et al., 2000; Ardizzone et al., 2007). A unique multi-temporal landslide inventory with 3391
97 landslides has been mapped in 19 different time slices. The age of the landslides ranges from relict and very old
98 landslides with an uncertain date of occurrence to landslides that have occurred in 2014. Aerial photographs, direct
99 geomorphological field mapping and satellite images were used for the preparation of the multi-temporal landslide
100 inventory (Ardizzone et al., 2013; Guzzetti et al., 2006a; Galli et al., 2008). Only time slices of the multi-temporal
101 inventory for which the relative date of occurrence is known (Figure 1), were used in this study because time
102 between landslides is a key element in the quantification of landslide path dependency (Samia et al., 2017a, b). In
103 addition, the first time slice, with the known date of 1939, was only used in the computation of the landslide path
104 dependency parameters, and not in landslide susceptibility modelling because of its unknown past. Ultimately, a
105 multi-temporal landslide inventory was used that contains distribution of landslides in 16 time slices dating from
106 1947 to 2014 (Figure 1). This multi-temporal landslide inventory was mostly prepared at the scale of 1:10,000
107 which is sufficient for conversion to a 10 × 10 m pixel-based landslide inventory. However, time slices from 1939
108 to 1997 were prepared from aerial photographs with scales ranging from 1:15,000 to 1:33,000, and this may
109 introduce some positional inaccuracy in landslides, in the order of one pixel. Given that the median size of landslide
110 in this period is 19 pixels, we believe that this is an acceptable level of inaccuracy.

111 More information about the Collazzone study area and the multi-temporal landslide inventory is given in (Galli et
112 al., 2008; Guzzetti et al., 2006a; Guzzetti et al., 2009; Ardizzone et al., 2007).



113
114 **Figure 1.** Multi-temporal landslide inventory dating from 1939 to 2014 (left map) (adapted from (Samia et al.,
115 2018; Samia et al., 2017a, b)). Collazzone study area and Umbria region (right upper map). The coordinate system
116 of maps is EPSG:32633 (www.spatialreference.org). Landslide points were constructed by placing a point in the
117 geometric centre of each landslide polygon (map in the right lower corner). The red rectangle shows the extent of
118 the map in the lower right.



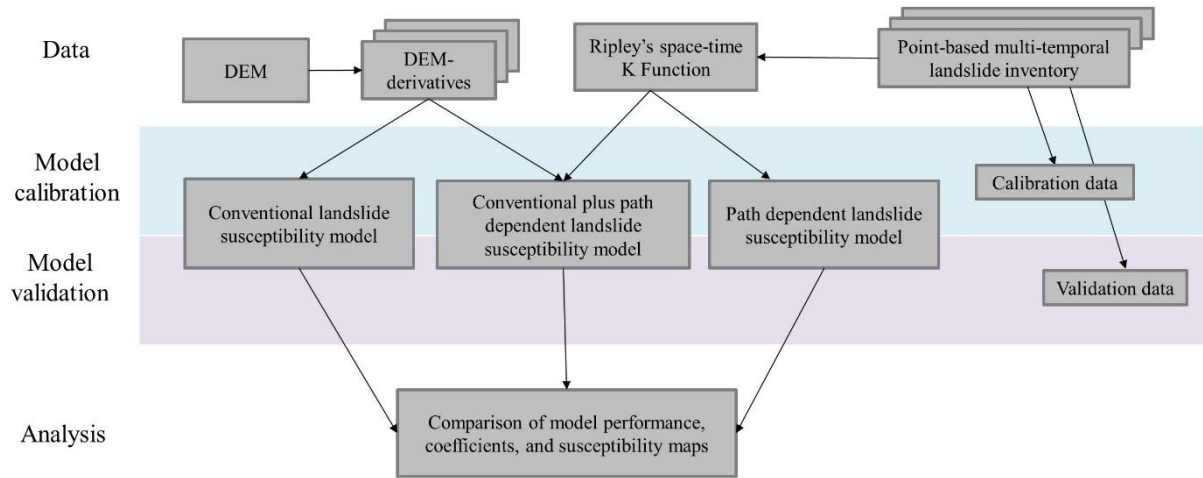
119

120 **Figure 2.** DEM (digital elevation model) and its derivatives used in conventional and conventional plus path
 121 dependent landslide susceptibility models. TPI means topographic position index, TWI means topographic wetness
 122 index and LS factor stands for slope length and steepness factor.

123 **3. Methods**

124 We used logistic regression to construct three different landslide susceptibility models (Figure 3): (i) a
 125 conventional landslide susceptibility model using DEM-derivatives, (ii) a conventional plus path dependent
 126 landslide susceptibility model using 16 DEM-derivatives and two landslide path dependency variables (explained
 127 below), and (iii) a purely path dependent landslide susceptibility model using only the two landslide path
 128 dependency variables. We compared the performance of these models using Area Under Curve (AUC) values from
 129 the Receiver Operating Characteristic (ROC) (Mason and Graham, 2002), and selected the optimal model using

130 the Akaike Information Criterion (AIC) (Akaike, 1998), which penalizes the use of additional variables in a model.
 131 Ultimately, the coefficients of the variables selected by three landslide susceptibility models and the resulting
 132 landslide susceptibility maps were compared.



133 **Figure 3.** Flowchart of methods

134

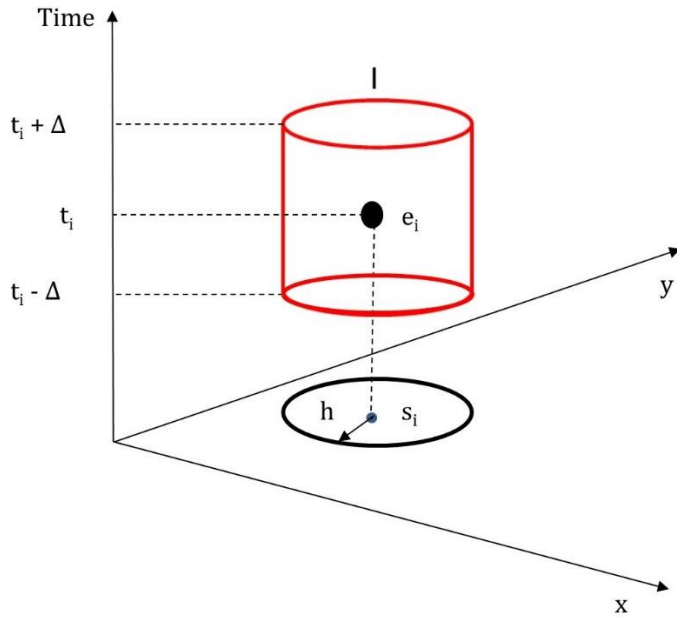
135 3.1 Quantifying landslide path dependency using Ripley's space-time K function

136 The spatial-temporal dynamics of landslide path dependency was recently quantified for the Collazzone study area
 137 (Samia et al., 2017a), and was implemented in landslide susceptibility modelling at the scale of slope units (Samia
 138 et al., 2018). Our previous quantification of landslide path dependency used simplified information about the
 139 spatial overlap among landslides in a polygon-based multi-temporal landslide inventory (Samia et al., 2017b). The
 140 novel aspect of the present paper is that now, at finer spatial resolution, we quantify landslide path dependency
 141 simultaneously in space and time. For this quantification, we use Ripley's K function (Ripley, 1976; Diggle et al.,
 142 1995). Ripley's K function has been used mainly in spatial point pattern analysis and reflects the degree of spatial
 143 clustering of events (e.g., landslides (Tonini et al., 2014), forest fire (Gavin et al., 2006), crimes (Levine, 2006)
 144 and disease outbreaks (Hinman et al., 2006)). The function determines whether events are clustered, dispersed or
 145 randomly distributed. A modified Ripley's K function was also used to quantify the degree of clustering of point
 146 events in space and time (Lynch and Moorcroft, 2008; Ye et al., 2015). In the landslide path dependency context,
 147 we used Ripley's space-time K function to reflect the degree to which landslides occur near previous landslides,
 148 and how this changes with increasing distance to the previous landslide in space and time. The starting point to
 149 derive Ripley's K is a point-based multi-temporal landslide inventory consisting of points in the geometric centre
 150 of polygons of landslides (Figure 1).

151 Ripley's space-time K function tests whether the number of events that is observed in a space-time cylinder around
 152 an initial event is equal to what is expected given the average point density in space and time (Ripley, 1976, 1977;
 153 Diggle et al., 1995). The space-time cylinder $I_{(h, \Delta)}$ (Figure 4) is defined as:

$$154 I_{(h, \Delta)}(d_{ij}, t_{ij}) = \begin{cases} 1, & (d_{ij} \leq h \text{ and } (t_{ij} \leq \Delta)) \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

155 where h shows the spatial distance increment, Δ shows the time increment, i and j are two landslide centre points,
 156 and d and t reflect the distance and time between the two landslide centre points, respectively.



157 **Figure 4.** Space-time cylinder neighbourhood (Smith, 2016) for a landslide event (e_i)

158 The expected Ripley's K function for one space-time cylinder of size h and Δ is defined as:

159
$$K(h, \Delta) = \frac{1}{\lambda_{st}} \sum_{j \neq i} E[I_{(h, \Delta)}(d_{ij}, t_{ij})] \quad (2)$$

160 where E is the expected number of landslides in the cylinder, and λ_{st} reflects the average space-time intensity of
 161 the landslides i.e., the expected number of landslides per unit of space-time volume, which is calculated as:

162
$$\lambda_{st} = \frac{n}{a(R) \times (t_{max} - t_{min})} \quad (3)$$

163 where n is the number of landslides in the entire inventory, t is time, and $a(R)$ reflects the size of the area. Therefore,
 164 the expected Ripley's space-time K function for the space-time cylinders around each landslide point is defined
 165 as:

166
$$K(h, \Delta) = \frac{1}{n \cdot \lambda_{st}} \sum_{i=1}^n \sum_{j \neq i} E[I_{(h, \Delta)}(d_{ij}, t_{ij})] \quad (4)$$

167 Similarly, the observed Ripley's space-time K function is calculated from the landslide inventory as:

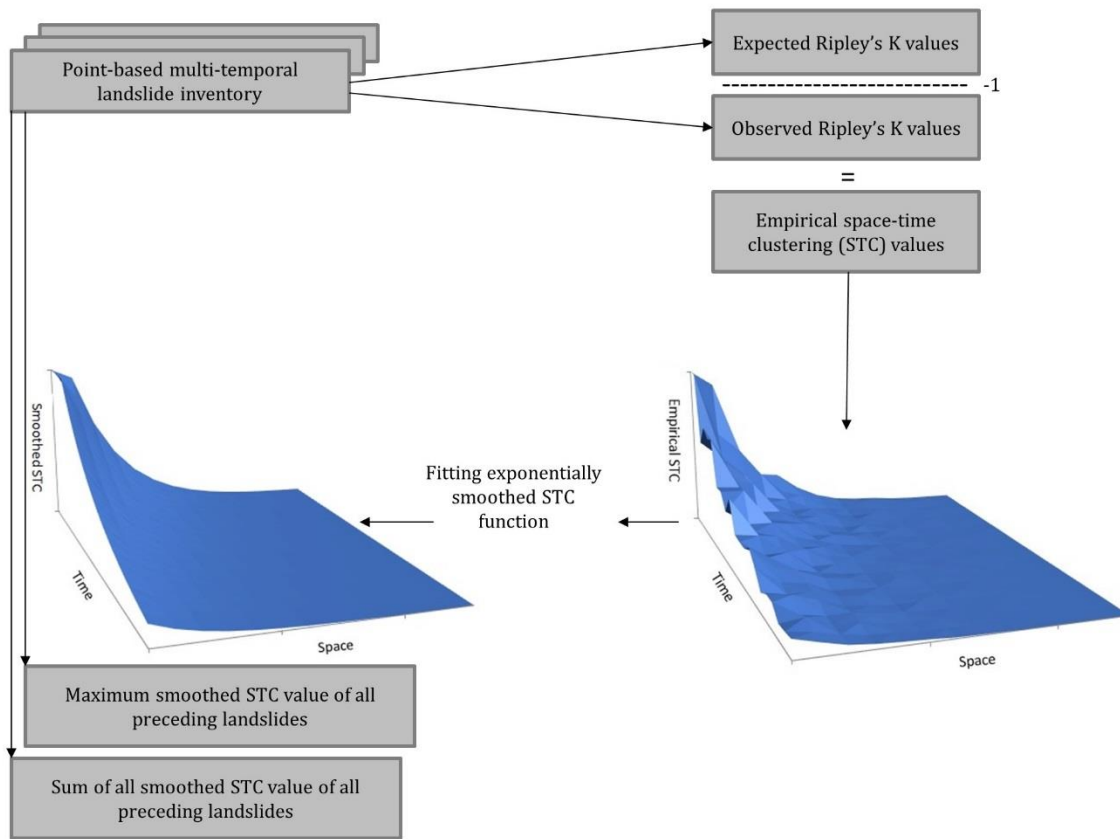
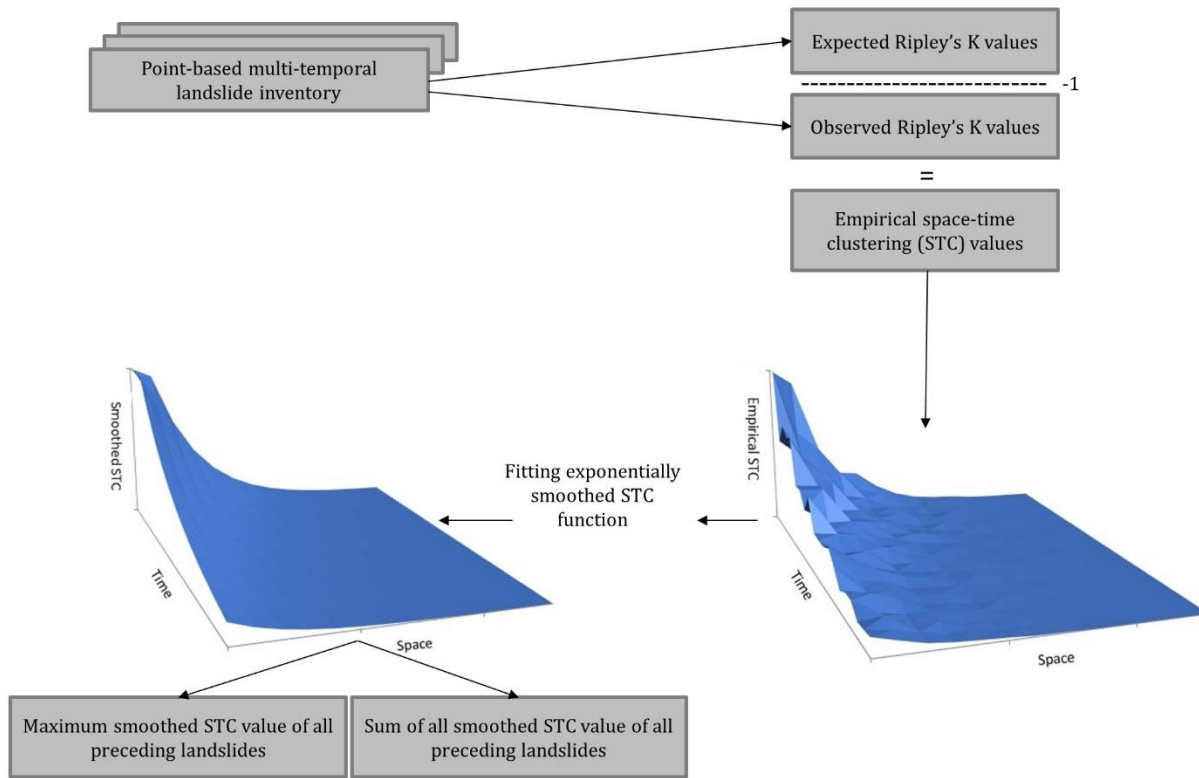
168
$$\hat{K}(h, \Delta) = \frac{1}{n \cdot \lambda_{st}} \sum_{i=1}^n \sum_{j \neq i} I_{(h, \Delta)}(d_{ij}, t_{ij}). \quad (5)$$

169 Finally, we defined the space-time clustering (STC) measure, which reflects how much more likely it is that a
 170 landslide will occur given a time and space distance from a previous landslide, as following:

171
$$\text{Empirical } STC(h, \Delta) = \frac{\hat{K}(h, \Delta)}{K(h, \Delta)} - 1 \quad (6)$$

172 STC values > 0 indicate clustering and values < 0 indicate dispersion. We calculated STC (h, Δ) for a wide range
173 of h and Δ : values of h ranged from 0 to 500 meter in 30 steps, and values of Δ ranged from 0 to 38 years in 30
174 steps. This yielded 900 empirical values of STC (h, Δ). We then fitted an exponential decay function of h and Δ to
175 the empirical STC values. This exponential decay function was used to calculate STC values for each pixel
176 depending on when and where a landslide last occurred closely to that pixel.

177 Based on this, we calculated two landslide path dependency variables (Figure 5). The first variable reflects the
178 maximum value of all STC values for all previous landslides near a pixel. This variable results in high values when
179 one particular previous nearby landslide is expected to have a large impact on the susceptibility of landsliding. The
180 second variable is the sum of all STC values of all previous landslides near a pixel. This variable results in high
181 values when all previous nearby landslides are expected to have a large impact on the susceptibility of landsliding.
182 This approach mirrors what we did in our slope unit-based susceptibility model (Samia et al., 2018) in the sense
183 that the variables separate the impact of the most impactful previous nearby landslide from the impacts of all
184 previous nearby landslides.



185 **Figure 5.** Procedure to compute the two landslide path dependency variables using Ripley's space-time K function.

186 **3.2 Logistic regression**

187 Logistic regression is considered a reference model in statistically-based landslide susceptibility modelling
188 (Reichenbach et al., 2018). Relations between presence and absence of landslides as a binary target variable are
189 explained by a set of independent variables such as slope steepness and slope position in logistic regression. In
190 this paper, DEM-derivatives (section 2 and Figure 2) as well as the two landslide path dependency variables
191 computed using the Ripley's space-time K function (see section 3.1) were used as independent variables. Landslide
192 presence or absence was the binary target variable.

193 **3.3 Training and testing**

194 When using a multi-temporal landslide inventory in landslide susceptibility modelling, the selection of time slices
195 for the training and testing is crucial. In Rossi et al. (2010) and Samia et al. (2018), a sequential splitting sampling
196 strategy was used in such a way that landslides in older time slices were used to train the model and landslides in
197 newer time slices were used to test the model. However, such a sequential sampling strategy does not provide an
198 equal range of landslide histories between training and testing datasets and this could bias the role of time in path
199 dependent landslide susceptibility modelling. To avoid such a timing inequality, Samia et al. (2018) also
200 introduced a non-sequential sampling strategy in which the span of timing segregation among time slices in the
201 training and the testing datasets is comparable. In this study, we used this sampling strategy to split the multi-
202 temporal landslide inventory into training and testing datasets. To achieve this, all landslides in the time slices of
203 1947, 1954, 1981, 1985, 1999, May 2004, March and May 2010 were used for training, and all landslides in the
204 time slices of 1965, 1977, 1991, 1997, December 2004 and 2005 and April 2013 and 2014 were used for testing
205 (Figure 1).~~To achieve this, landslides in the time slices of 1947, 1954, 1981, 1985, 1999, May 2004, March and~~
206 ~~May 2010 were used for training, and landslides in the time slices of 1965, 1977, 1991, 1997, December 2004 and~~
207 ~~2005 and April 2013 and 2014 were used for testing (Figure 1).~~ It is important to note that the time slice in 1939
208 was used only for quantification of landsliding history of the other time slices, and not for training or testing. Thus,
209 the 1st time slice in the training dataset is 1947 (Figure 1).

210 The number of pixels with landslides was smaller than the number of pixels without landslides in both training
211 and testing datasets. Therefore, we randomly selected 5,000 pixels with landslides and 5,000 pixels without
212 landslides from both training and testing datasets in order to create equal datasets both for training and testing of
213 the models. This random selection of pixels was repeated 10 times both in the training and testing datasets.
214 Therefore, we trained the conventional, conventional plus path dependent and purely path dependent landslide
215 susceptibility 10 times, and finally tested 10 times as well. After preparation of the 10 training datasets, logistic
216 regression was applied to the 10 training datasets with entry probability of 0.05 and removal probability of 0.06 for
217 independent variables to diminish the chance of overfitting in the model. We only allowed inter-variable
218 correlations less than 0.8 to avoid multicollinearity. Conventional landslide susceptibility was modelled using
219 DEM-derivatives only once for the defined training dataset and was tested using the independent testing dataset.
220 Conventional plus path dependent landslide susceptibility model was constructed using DEM-derivatives plus the
221 two landslide path dependency variables. The purely path dependent landslide susceptibility was modelled only
222 by using the two landslide path dependency variables. All three models were constructed only once. Model

223 performance was assessed using AUC and AIC values. The AUC values for testing were assessed using 10 training
 224 models and 10 independent testing datasets. The models with highest performance in terms of AUC values, were
 225 used to map susceptibility to landslides. Finally, we compared landslide susceptibility maps resulting from
 226 conventional, conventional plus path dependent and purely path dependent susceptibility.

227 4. Results

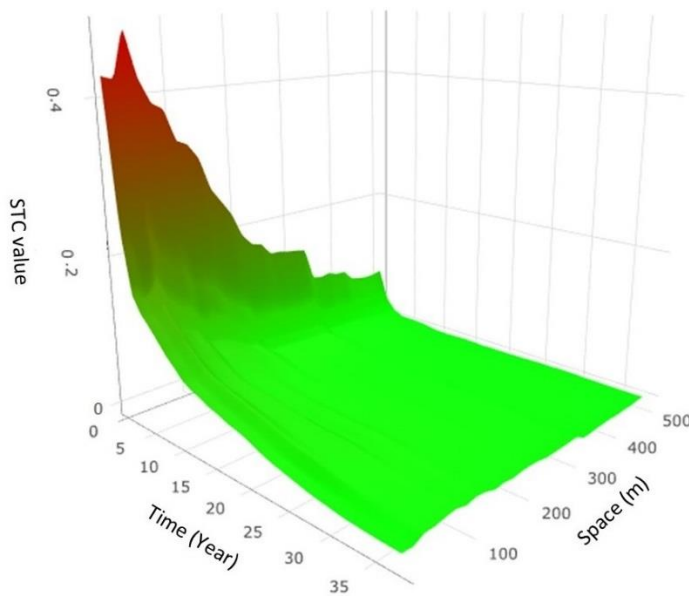
228 4.1 Spatial-temporal dynamic of landslide path dependency

229 Ripley's space-time K function confirmed the existence of landslide path dependency at small spatial and small
 230 temporal distances from a previous landslide (Figure 6). The STC measure (Eq 6) is high in the space-time vicinity
 231 of an earlier landslide, and it then decreases rapidly. Apparently, landslide susceptibility is relatively high
 232 immediately after occurrence of an earlier, nearby landslide.

233

234

235



236 **Figure 6.** Space-time dynamic of landslide path dependency. The colours represent the intensity of STC measure.
 237 Red color indicates high STC and green indicates low STC.

238 The exponential decay function that was fitted to the empirical STC values is:

239
$$\text{Smoothed STC}(t, d) = 0.44 * e^{(-t/16.7)} * e^{(-d/58.8)} \quad (7)$$

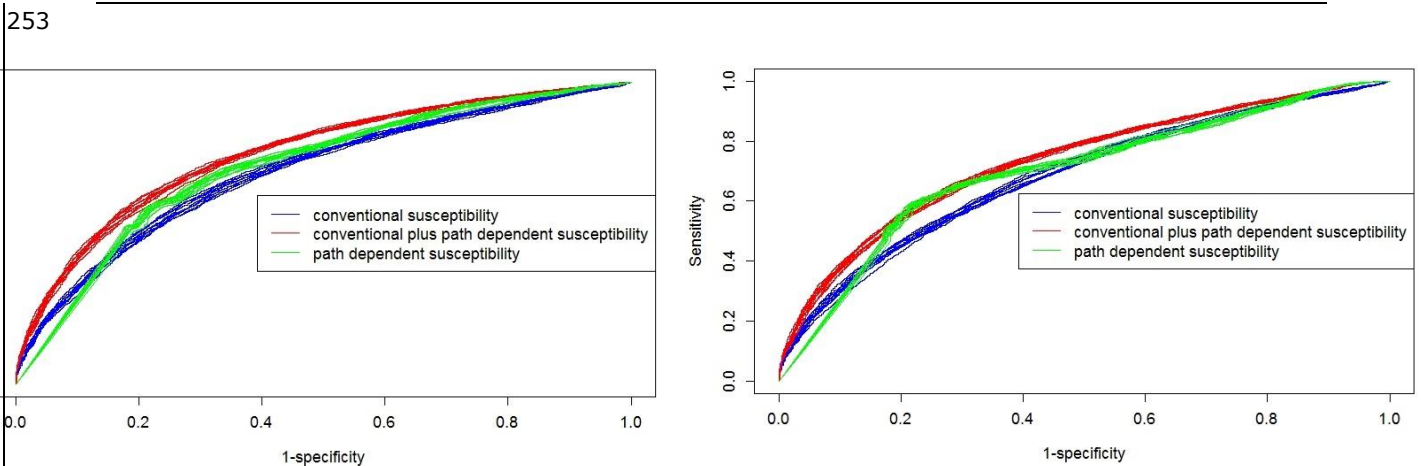
240 This function shows that the STC measure decays exponentially over a characteristic time scale of 16.7 years and
 241 characteristic spatial scale of 58.8 meters. The residual standard error of the exponential function is 0.01, in units
 242 of STC (-), which compares favourably with the actual values that range up to 0.44.

243 4.2 Model performance

244 We compared performance of the conventional, conventional plus path dependent, and purely path dependent
 245 landslide susceptibility models, using AUC (greater is better) and AIC (lower is better) values as measure of
 246 performance. The best performing landslide susceptibility model was the conventional plus path dependent model,
 247 both when expressed as AUC values and as AIC values (Table 1). The purely path dependent landslide
 248 susceptibility model, constructed with only the two landslide path dependency variables, performed better than the
 249 conventional landslide susceptibility model with its 16 DEM-derived variables.

250 **Table 1.** Performance of the three landslide susceptibility models. The values of AUC represent the average AUC
 251 values in the 10 training and 10 testing datasets. The values of AIC represent the average AIC values in the 10
 252 training datasets.

AUC and AIC values	Conventional susceptibility model	Conventional plus path dependent susceptibility model	Path dependent susceptibility model
AUC training	0.704 ± 0.006	0.764 ± 0.003	0.721 ± 0.004
AIC training	12,678 ± 82	11,711 ± 53	12,469 ± 62
AUC testing	0.682 ± 0.007	0.732 ± 0.004	0.698 ± 0.004



254 **Figure 7.** Receiver operating characteristic (ROC) curves of the three landslide susceptibility models in the 10
 255 training datasets (left) and in the 10 testing datasets.

256 For conventional susceptibility models, 6 DEM-derivatives were selected in all 10 models (Table 2). Adding two
 257 landslide path dependency variables into DEM-derivatives variables affected the inclusion and exclusion of DEM-
 258 derivative variables only slightly. For example, the variables TPI and distance to river were selected 4 and 7 times
 259 respectively in the conventional susceptibility models whereas after adding the two landslide path dependency
 260 variables, these variables were selected 5 and 4 times respectively. The variable eastness which was selected twice
 261 in the conventional susceptibility models, was never selected in the conventional plus path dependent susceptibility
 262 models.

263

264

265 **Table 2.** Selection of independent variables in conventional, conventional plus path dependent and purely path
 266 dependent landslide susceptibility modelling. Variables selected 6 or more times are shown. The numbers between
 267 parentheses indicate how often variables were selected.

Three landslide susceptibility models	Number of variables selection in 10 times repetition	Average number of variables selected in the three susceptibility models
Conventional (16 DEM-derivatives)	Elevation (10), standard deviation of slope (10), LS factor (10), standard deviation of elevation (10), stream power index (10), aspect (10), distance to river (7), vertical distance to channel network (6), relative slope position (6)	8.7
Conventional plus path dependent (16 DEM-derivatives plus two landslide path dependency variables)	Elevation (10), standard deviation of slope (10), LS factor (10), standard deviation of elevation (10), stream power index (10), aspect (10), max smoothed STC value (10), sum of all smoothed STC value (10)	10.4
Path dependent (two landslide path dependency variables)	max smoothed STC value (10), sum of all smoothed STC value (10)	2

268

269 In all the training and the testing datasets, the contingency tables (Table 3) showed that conventional landslide
270 susceptibility models differed substantially from the conventional plus path dependent and path dependent
271 landslide susceptibility models. In particular, the percentage of false positives (the percentage of pixels without
272 landslides predicted with landslides) for the conventional susceptibility models is higher than for the two other
273 susceptibility models. However, there are also fewer true negatives (the percentage of pixels without landslides
274 predicted without landslides) in the conventional than in the conventional plus path dependent and path dependent
275 susceptibility models. The variation in the differences is larger in the training datasets than the testing datasets,
276 suggesting that all fitted models are robust.

277

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283 **Table 3.** Contingency tables computed with cut off value of 0.5 for the three models. The numbers in the table
284 represent the average values computed in the 10 training and 10 testing datasets.

		Conventional landslide susceptibility		Conventional plus path dependent landslide susceptibility		Path dependent landslide susceptibility	
		Observed landslides		Observed landslides		Observed landslides	
		yes	no	yes	no	yes	no
Predicted landslides (training)	yes	35 ± 0.33	19 ± 0.60	34 ± 0.42	14 ± 0.23	31 ± 0.8	13 ± 0.32
	no	15 ± 0.33	31 ± 0.60	16 ± 0.42	36 ± 0.23	19 ± 0.8	37 ± 0.32
Predicted landslides (testing)	yes	33 ± 0.50	19 ± 0.21	29 ± 0.35	13 ± 0.43	23 ± 0.24	12 ± 0.41
	no	17 ± 0.50	31 ± 0.21	21 ± 0.35	37 ± 0.43	27 ± 0.24	38 ± 0.41

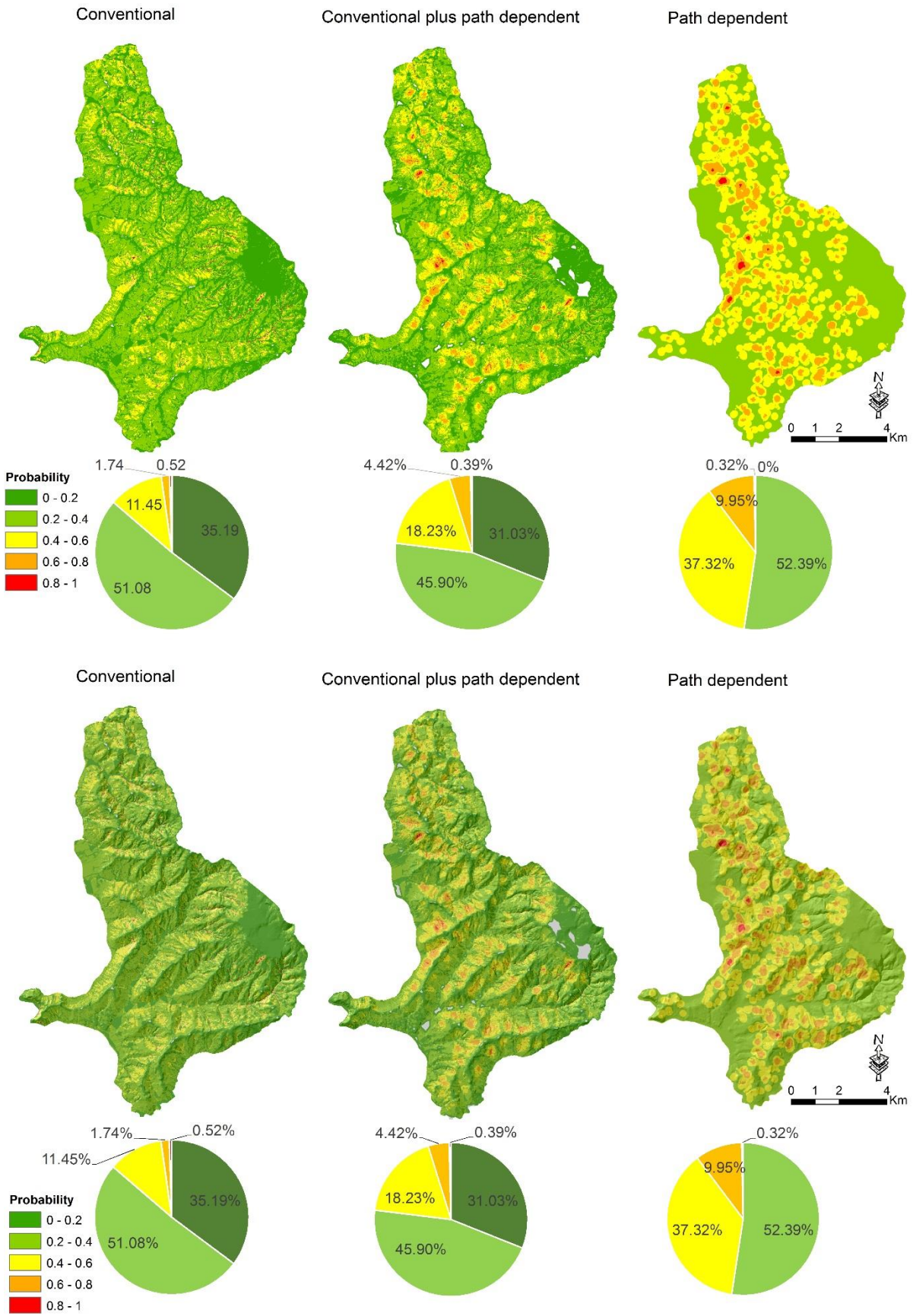
285

286 **3.3 Conventional, conventional plus path dependent and purely path dependent landslide susceptibility**
287 **maps**

288 The landslide susceptibility maps derived from the three models illustrate different patterns of landslide
289 susceptibility (Figure 78). For the models that include path dependency, the presented maps give the average values
290 of all simulated time slices. Differences between the maps correspond with the considerable differences in the
291 performance of their landslide susceptibility models in terms of AUC and AIC values (Table 1). The path
292 dependent landslide susceptibility map is visually different from both other landslide susceptibility maps, with the
293 pattern dominated by regions of high susceptibility around locations where landslides previously occurred.

294

295

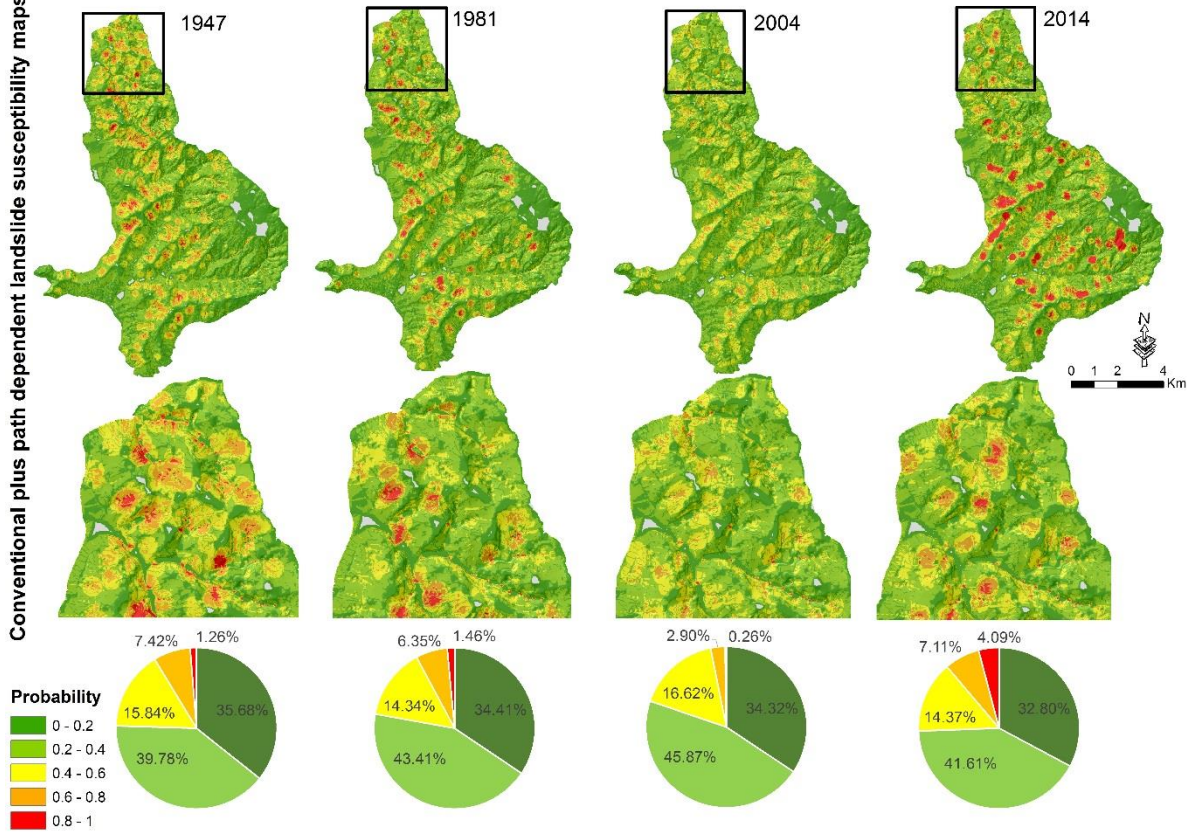


296 **Figure 78.** Conventional landslide susceptibility map in the left, the conventional plus path dependent landslide
 297 susceptibility map (averaged out over 16 time slices) in the middle and path dependent landslide susceptibility

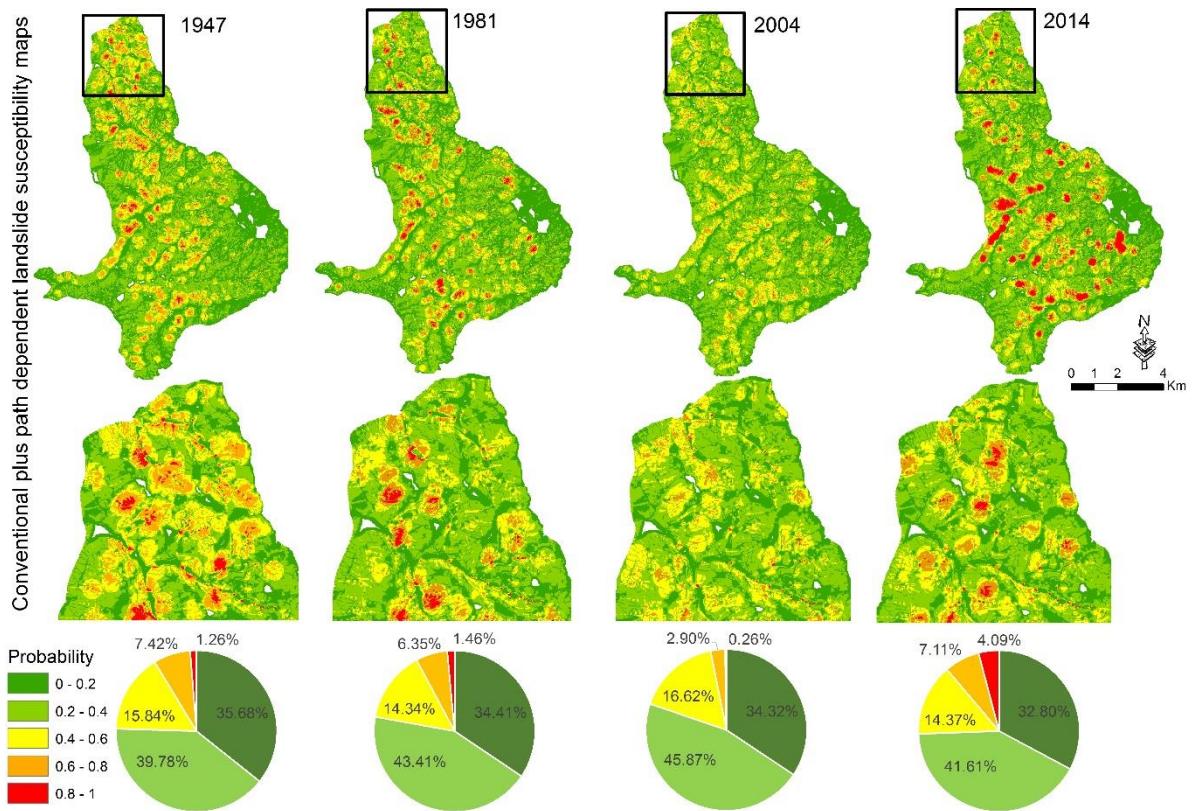
298 map (averaged out over 16 time slices) in the right. The pie charts show the percentage of pixels in each map in
299 different probability levels of landslide occurrence.

300 The 16 conventional plus path dependent landslide susceptibility maps are dynamic and change over time (Figure
301 [89](#)). These changes reflect the exponential decay with increasing time since previous nearby landslides (Figure 6)
302 and the sudden increase of susceptibility in areas close to recent landslides. The gradual decrease in susceptibility
303 levels is clearest when comparing the 1981 and 2004 susceptibility maps, whereas the sudden increase is clearest
304 when comparing the 2004 and 2014 maps. The 2014 susceptibility map has higher susceptibility levels because of
305 the impact of recent landslides in the year 2013.

Conventional plus path dependent landslide susceptibility maps

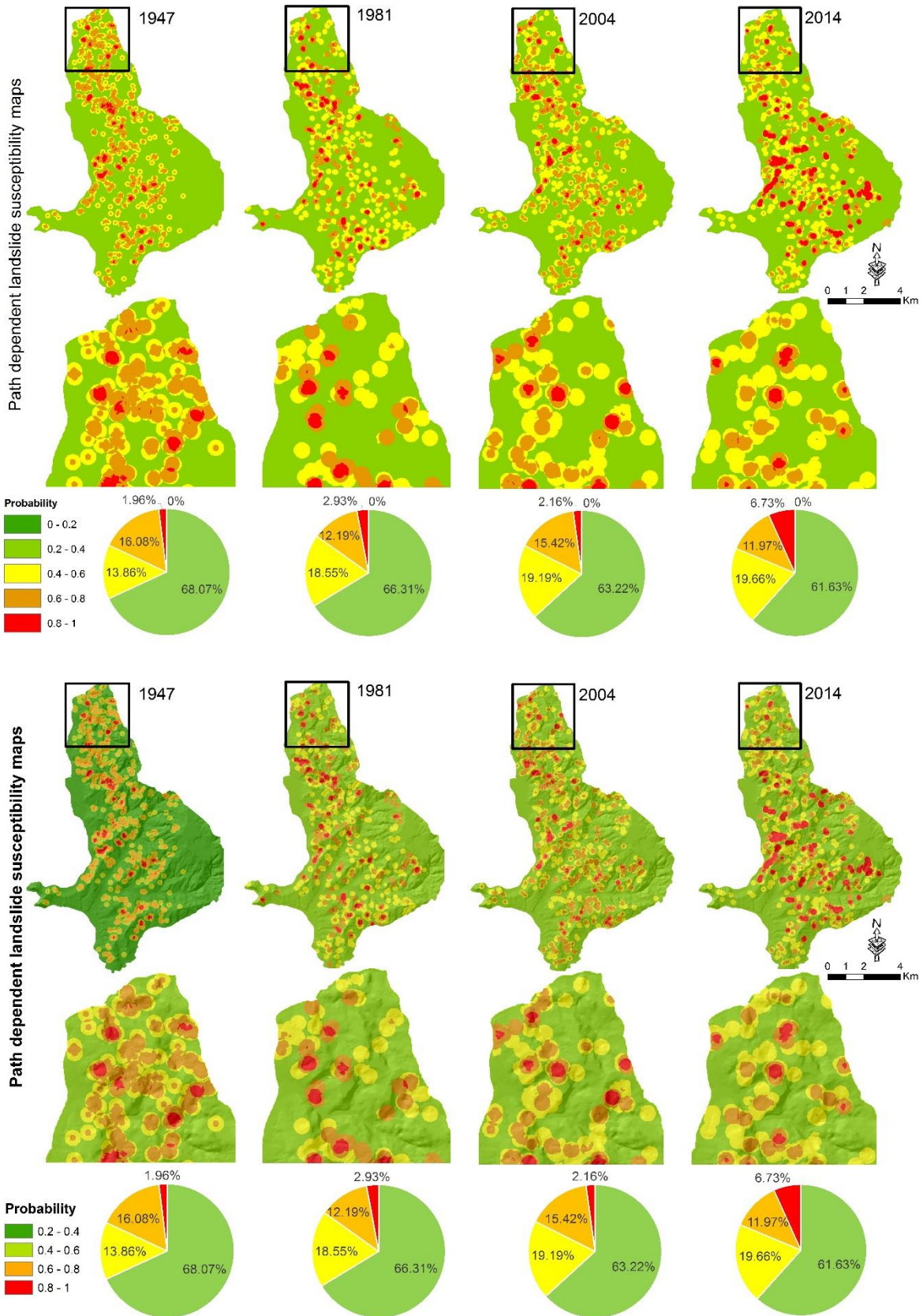


Conventional plus path dependent landslide susceptibility maps



307 **Figure 89.** Examples of four dynamic conventional plus path dependent landslide susceptibility maps in the years
308 of 1947, 1981, 2004 and 2014. Zoomed maps show the places where there are large changes in susceptibility over
309 time.

310 Similar dynamics are visible when comparing landslide susceptibility maps constructed with the purely path
311 dependent model for different years (Figure 910). These maps show only the pure influence of earlier landslides
312 on susceptibility to future landslides (Figure 6). Again, the susceptibility of landslides decreases where distance
313 from earlier landslides in space and time increases, but jumps back up when more recent landslides become part
314 of the landslide history. The pure influence of each individual landslide on the susceptibility to the future landslide
315 is strong when a landslide is fresh which is reflected in the high percentage of susceptibility levels of 0.6-0.8 and
316 0.8-1.0 in 1947 and 2014. When time passes since the previous landslide has occurred, the susceptibility decreases
317 with an exponential decay response which is reflected in the low percentage of susceptibility levels of 0.6-0.8 and
318 0.8-1.0 in 1981 and 2004.



319 **Figure 910.** Examples of four dynamic path dependent landslide susceptibility maps in the years of 1947, 1981,
 320 2004 and 2014. Zoomed maps show the places where there are large changes in susceptibility over time.

321 **5. Discussion**

322 In this section, we focus first on the quantification of landslide path dependency in the pixel-based multi-temporal
323 landslide inventory, and then discuss its role in susceptibility models. We also discuss the susceptibility model
324 performance for all three model types. At the end, the exportability of landslide path dependency parameters and
325 the implication of dynamic time-variant path dependent landslide susceptibility in landslide hazard is discussed.

326 **5.1 Quantification of landslide path dependency**

327 The quantification of landslide path dependency using Ripley’s space-time K function (Ripley, 1976; Diggle et
328 al., 1995) indicates, in our study area, an exponential decay response in the STC values (Figure 6). This means
329 that there is a positive influence of earlier nearby landslides on susceptibility that decays exponentially in time and
330 space with a characteristic time scale of about 17 years, and a characteristic space scale of about 60 meters. This
331 is in accordance with our previously quantified landslide path dependency using follow-up landslide fraction in
332 which the decay period of landslide path dependency was found to be about two decades (Samia et al., 2017b).
333 Landslide clustering manifests in the form of spatial association among landslides where follow-up landslides
334 occur immediately after and close to a previous landslide (Samia et al., 2017a). Samia et al. (2017b) discussed the
335 possible mechanism in the formation of clusters of landslides in which the size of the initial landslide and changes
336 in hydrology of slope destabilized by a landslide could facilitate the occurrence of follow-up landslides and hence
337 clusters of landslides.

338 STC values and their exponential decay to some extent depend on the method that we have chosen to determine
339 the centre point of landslides when converting polygons of landslides to points of landslides. Our approach was to
340 take the geometric centre, but other options exist (Haines, 1994) and their impact should be explored. Also, in the
341 computation of STC values with Ripley’s space-time K function, distance between landslides was calculated using
342 the Pythagorean theorem without distinguishing between distances in the x and y direction. Also we did not include
343 differences in the elevation of centre points in our distance calculations. For future work, it could be interesting to
344 define one dimension as the distance along the slope in the downslope direction and another dimension as the
345 distance in the slope parallel direction, and keeping these two spatial dimensions separate in addition to the
346 temporal dimension.

347 **5.2 Effect of landslide path dependency on performance of landslide susceptibility models**

348 Our results demonstrated that including landslide path dependency effect in a pixel-based landslide susceptibility
349 model constructed by DEM-derivatives improves model performance substantially. This is in line with high AUC
350 and low AIC values for the conventional plus path dependent landslide susceptibility model (Table 1 [and Figure](#)
351 [7](#)). This confirms our main hypothesis that adding the effect of landslide path dependency boosts the performance
352 of landslide susceptibility models, and is in accordance with our previous expectations regarding stronger effect
353 of landslide path dependency in a pixel-based landslide susceptibility model than in a slope unit-based landslide
354 susceptibility model (Samia et al., 2018). Landslide path dependency is a local effect (apparently with
355 characteristic space scale of about 60 meters) in which an earlier landslide increases the likelihood of follow-up
356 landslide occurrence. Such a local effect is obviously more visible at pixel resolution of 10 m rather than at slope
357 unit resolution (with a median size of 51486 m² in our study area).

358 Strikingly, the purely path dependent landslide susceptibility model constructed with only the two landslide path
359 dependency variables performs better than the conventional landslide susceptibility model made by DEM-
360 derivative variables (Table 1 and Figure 7). This is potentially interesting since it implies that the landslide
361 inventory itself can be used to map susceptibility to landslide without using DEM-derivatives which have been
362 conventionally used in landslide susceptibility modelling (Varnes, 1984; Guzzetti et al., 2005). The performance
363 of this path dependency-only model thus highlights that proximity to previous landslides can adequately capture
364 susceptible locations. It also suggests that the path dependent models' success in our experiments may be partly
365 due to the fact that they capture static spatial effects that have not been resolved with our explanatory factors. It is
366 attractive to imagine follow-up work that attempts to disentangle this static spatial effect that is unrelated to
367 landslide history from dynamic spatial effects that are related to landslide history. The key to such disentangling
368 should be that the former does not decay over time, whereas the latter does. More advanced statistical approaches
369 that simultaneously estimate purely spatial and spatiotemporal effects may be needed. More complex explanatory
370 variables such as geology, soil and land use can also be used along with DEM-derivatives to improve landslide
371 susceptibility models and maps. However, these are not always available. In fact, considering landslide path
372 dependency effect into such complete explanatory factors improve their performance as well. We confirmed this
373 in an additional exploration where we constructed a conventional landslide susceptibility model used in this paper,
374 with the same DEM-derivatives, but also with land use and geology as explanatory factors. The results
375 demonstrated that adding our two landslide path dependency variables to such an improved conventional landslide
376 susceptibility increased its performance (from AUC value of 0.771 to AUC value of 0.801).

377 Another important aspect of considering landslide path dependency effect in landslide susceptibility modelling is
378 providing dynamic landslide susceptibility maps. Landslide susceptibility maps are usually classified into five
379 levels of probability to landslide occurrence ranging from 0 to 1. In the conventional landslide susceptibility map
380 (Figure 78, right-left map), the five probability levels of susceptibility by definition remain constant over time
381 since the DEM-derivatives in the model are constant (although DEM-derivatives also change when a landslide
382 occurs, but DEMs are not updated frequently enough to reflect this). The usage of conventional static landslide
383 susceptibility maps and dynamic landslide susceptibility maps taking landslide path dependency depends
384 on the goal and task of audience. In reality, static susceptibility maps created (either with a conventional
385 susceptibility model, or as the static portion of a conventional plus path dependent model) with this time-insensitive
386 method are can be used in sustainable planning whereas dynamic susceptibility maps can be considered in short-
387 term land use planning. only for an amount of time roughly equal to the temporal length of the original landslide
388 inventory.

389 However, adding landslide path dependency in landslide susceptibility models, provides dynamic landslide
390 susceptibility maps (Figures 8-9 and 910) in which the levels of susceptibility change over time, reflecting the
391 exponential decay response of landslide path dependency (Figure 6). The changes are in the places where
392 landslides have already occurred, mainly in probability levels of susceptibility ranging from 0.6 to 1.0. This
393 suggests that the part of area located in the high probability level of susceptibility could switch to the low
394 probability level of susceptibility (0 to 0.6) after a decade. This is exemplified between 1947 and 1954 landslide
395 susceptibility maps, in which about 9 km² of study area drops more than 0.1 in their probability of landslide
396 occurrence. After adding the two path dependency variables in the conventional landslide susceptibility modelled

397 with DEM-derivatives, it turns out that the coefficients of all DEM-derivative variables become lower (e.g., LS
398 factor becomes less important).

399 **5.3 Can landslide path dependency parameters be transported to other areas?**

400 In landslide prone areas where landslides are documented and mapped in the form of polygon-based multi-
401 temporal inventories, the landslide path dependency can be quantified based on geographical overlap among
402 landslides, and hence used in landslide susceptibility modelling (Samia et al., 2017b; Samia et al., 2018). However,
403 polygon-based multi-temporal landslide inventories are rare to the best of our knowledge, and hence in many areas
404 geographical overlap among landslides cannot be computed. In this paper, we proposed using Ripley's space-time
405 K function to compute landslide path dependency where point-based multi-temporal landslide inventories are used.
406 Using such inventories, our STC measure (Eq. 6) can be used to quantify path dependency among landslides.

407 It is attractive to think that the STC measure (Eq. 6) and its parameters (Eq. 7) can be directly exported to landslide
408 prone areas with substantial geological and topographical similarities. However, to gain confidence in this
409 approach, multi-temporal landslide inventories from such places (e.g., (Schlögel et al., 2011)) need to be
410 interrogated to find out whether path dependency occurs, whether it occurs over similar space and time scales, and
411 whether it adds value to susceptibility modelling. This would also allow us to start exploring what determines the
412 characteristic space and time scales.

413 **5.4 Implications of path dependent landslide susceptibility in landslide hazard assessment**

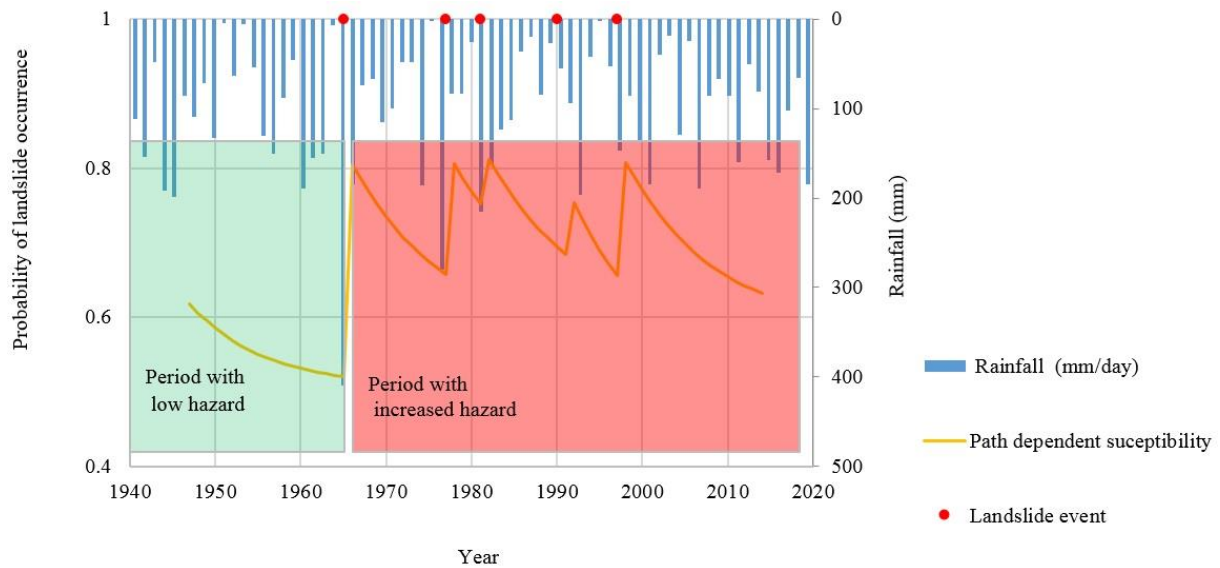
414 We have already modified the definition of conventional landslide susceptibility modelling (Varnes, 1984;
415 Guzzetti et al., 2005) using spatial temporal dynamics of landslide path dependency (Samia et al., 2017a, b) as
416 following:

$$417 \text{Landslide susceptibility}_{s,t} = f(\text{conditioning attributes}_s, \text{landslide path dependency}_{s,t}) \quad (8)$$

418 In this study, both conventional plus path dependent and path dependent landslide susceptibility models turned out
419 to perform better than a conventional landslide susceptibility model (Table 1 and Figure 7). In both models,
420 availability of a space-time component – reflecting the exponential decay of landslide path dependency – indicates
421 that landslide susceptibility is dynamic. This challenges the way landslide hazard is assessed as landslide
422 susceptibility is an important element of landslide hazard.

423 In landslide hazard assessment, landslide susceptibility as a proxy of 'where landslides occur' is combined with
424 the temporal probability of landslide triggers (mainly rainfall) to determine 'when landslides occur' (Guzzetti et
425 al., 2006a). In this context, a dynamic landslide susceptibility (Eq. 8) needs to be considered in combination with
426 the temporal information of landslide triggers in the assessment of landslide hazard. When substantial landsliding
427 happens during a rainfall event, susceptibility in and around such landslides can be raised for a few decades in
428 which moderate rainfall events may already cause substantial landsliding, which raises susceptibility levels again.
429 (Figure 4011). Such dynamics have been observed in a site near Seattle, Washington, where several new landslides
430 occurred in a slope that had recently experienced landslide activity whereas a nearby hillslope with the same
431 characteristics but without recently landslide activity did not experience new landsliding (Mirus et al., 2017). If no
432 substantial triggering event happens over the characteristic time scale of roughly 17 years, the increased

433 susceptibility will be substantially reduced, and a later rainfall event may have less influence on landsliding; the
434 probability of experiencing a follow-up landslide will have decreased.



435 **Figure 1011. Hypothetical example Conceptual model** of the implication of dynamic path dependent landslide
436 susceptibility model in landslide hazard assessment. When susceptibility is low, the hazard is also low (providing
437 the other components of landslide hazard e.g., size remain unchanged) and large rainfall events are needed to
438 trigger new landslides. Then, when susceptibility is raised by such landslides, the hazard is also high and small
439 rainfall events may trigger new landslides.

440 6. Conclusion

441 In the Collazzone study area, in Central Italy, quantification of landslide path dependency reveals an exponential
442 decay response in landslide susceptibility as a function of space and time distance to earlier nearby landslides. For
443 our study area, the characteristic time scale of this effect is about 17 years and the characteristic space scale is
444 about 60 meters. Adding such an exponential decay response of landslide path dependency in conventional pixel-
445 based landslide susceptibility modelled by DEM-derivative improves the performance of model substantially.
446 Taking into account landslide path dependency effects in landslide susceptibility results in dynamic landslide
447 susceptibility models where susceptibility changes over time. We stress that landslide susceptibility modelling
448 should take the effect of landslide path dependency into account since it provides an estimation of temporal
449 validation of different probability levels of landslide occurrence in landslide susceptibility map. The obtained
450 landslide path dependency parameters can possibly be used for dynamic landslide susceptibility modelling in
451 landslide prone areas with environmental and data similarities. We proposed a conceptual model that considers
452 the impact of dynamic path dependent landslide susceptibility on landslide hazard.

453 [Code and data availability. The multi-temporal landslide inventory, DEM, Geological and land use data of](#)
454 [Collazzone study area in Italy, was provided by CNR IRPI and can be requested from FG and FA. The code for](#)
455 [analysis of Ripley's space-time K function can be requested from JS and AT.](#)

456 [Author contributions. JS formulated the objective, designed the methodology and conducted the GIS, statistical,](#)
457 [space-time Ripley's analysis and modelling of landslide susceptibility. AT provided methodological support.](#)

458 advise and also made major revisions to the paper. AB and JW made major revisions to the paper. FG and FA
459 provided the data and also made major revisions to the paper.

460 Competing interests. The authors declare that they have no conflict of interest.

461

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