

1 ***Interactive comment on “Assessing the quality of landslide***
2 ***susceptibility maps – case study Lower Austria”***

3 ***by H. Petschko et al.***

4 ***Authors response on Referee #2 comments***

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11

12 **Reply to the specific comments**

13 We numbered the comments given by the referee, as some comments refer to similar sections
14 which were changed in the revised manuscript. This numbering should assist to make the
15 cross-references within this reply easier to follow.

16 The comments by the referee are presented in bold, whereas the reply is in normal font type.
17 The added text in the revised manuscript was inserted with an indentation. Please notice that
18 some comments were split up into more comments if the original comment was referring to
19 different lines or aspects. This is indicated with “...” at the end and at the beginning of the
20 comments concerned.

21 ***1. P1003 line 20 – 25: I suggest that the most used and applied models should be***
22 ***mentioned or briefly described. Then it would be easier to understand why they tend to***
23 ***overfit or why are they not flexible. This will enhance the manuscript and the methodology***
24 ***used.***

25 The reviewer correctly points out a source of confusion in the manuscript. Therefore, the most
26 commonly used models were briefly listed in the revised manuscript including some
27 references of studies using these methods. Within this the terms linear models and machine

1 learning models were explained by listing the most commonly used models found in literature
2 (e.g. logistic regression; artificial neural networks and support vector machines):

3 Added to page 1003, line 14

4 This study was embedded in a project preparing landslide susceptibility maps for the
5 province of Lower Austria (15.850 km²) with an aimed output map scale of 1:25,000
6 (Glade et al., 2012). Generally, landslide hazard zonation for determining slope
7 instability due to landslides is based on simple landslide inventories or heuristic,
8 statistical (including machine learning) or deterministic approaches (Soeters and Van
9 Westen, 1996). Although these approaches are dealing with landslide hazards (spatial
10 and temporal occurrence probability of landslides) the same categorization can be
11 applied for susceptibility maps. Statistical landslide susceptibility models are
12 particularly useful for modelling large areas on a medium scale (1:25,000 – 1:500,000)
13 to get an overview of which slopes or slope sections might be prone to landslides in
14 future (Fell et al., 2008). According to the resulting susceptibility maps hot spots can
15 be identified where more detailed analysis of the slope stability should follow (Van
16 Westen et al., 1997). For this study a statistical approach was regarded as suitable
17 considering the aimed output map scale, the size of the study area, the available data
18 and the limited availability of additional resources for preparing input data (such as
19 landslide inventory or soil parameters).

20 The central assumption of landslide susceptibility modelling is based on James
21 Hutton's (1726-1797) concept of uniformitarianism, "the past and the present are keys
22 to the future" (Orme, 2002). Thus, statistical estimation of the possible future location
23 of landslides is usually based on the conditions (e.g. local terrain attributes) of past
24 landslides (Varnes, 1984; Carrara et al., 1995). Presently, several statistical and
25 machine learning techniques are available for application to landslide susceptibility
26 modelling. The most common are logistic regression (Atkinson et al., 1998; Ayalew
27 and Yamagishi, 2005; Van Den Eeckhaut et al., 2006), bivariate models such as
28 weights of evidence (Neuhäuser and Terhorst, 2007; Schicker and Moon, 2012) and
29 machine learning techniques such as artificial neural networks (e.g. Nefeslioglu et al.,
30 2008; Pradhan and Lee, 2009) and support vector machines (e.g. Marjanović et al.,
31 2011; Pradhan, 2013).

1 **2. P1004 line 10 – 15: It should be clear why the *k*-fold validation is chosen and in**
2 **which grounds. The authors should quantify how much more reliable is this than**
3 **traditional methods. ...**

4 We understand the lack of background to the selection of the *k*-fold cross-validation. A more
5 detailed description of the differences of a single hold-out validation method to *k*-fold cross-
6 validation might assist for a deeper understanding. A single (non-replicated) hold-out
7 validation method is done with one single (random) sample and results in a single (random)
8 performance estimate whose particular value depends on (random) properties of the selected
9 training and test sets. While the hold-out set approach is, in principle, unbiased (on average
10 over many studies), it is known to be statistically inefficient in the sense that it has an
11 excessively large estimation variance. While we are unaware of any published quantification
12 of this inefficiency, it is clear that the precision of an estimator typically improves
13 asymptotically with the inverse of the square root of the sample size. Thus, choosing a large
14 number of cross-validation repetitions (here: $r = 20$) can be expected to reduce one
15 component of AUROC estimator precision (the component that is related to random variation
16 in cross-validation partitioning) by a factor of about 0.22 compared to a fixed partitioning in
17 single hold-out validation. In addition, using the entire data set (due to aggregation over all *k*
18 folds) instead of one fixed hold-out partition of (typically) 50% of the overall sample size is
19 further expected to improve the estimator's precision by a factor of 0.7. Since the focus of this
20 study is on model uncertainties and not on uncertainties in the estimation of model
21 uncertainties, we decided to omit such technical detail from the manuscript.

22 To explain the superiority of repeated *k*-fold cross-validation to the reader, the relevant part of
23 the Introduction section was moved to section 2.2 and has been modified as follows:

24 Added to page 1006, line 7

25 In single hold-out methods the data set is split in one single training and test sample.
26 The training sample is used to fit the model and the test sample is used to determine
27 the model performance. This results in a single estimate of the performance measure
28 (e.g. one single AUROC value) without providing a measure of precision of the
29 estimator. The estimate depends on the (random) sample used for modelling the
30 susceptibility and testing the model's performance, which may itself have "peculiar"
31 random characteristics that would be different for a different test set. Repeated *k*-fold
32 cross-validation solves this problem by using, one after another, different subsets or

1 partitions of the data set as test and training sets, thus effectively using the entire data
2 set for performance estimation (Brenning, 2012a, 2012b). In addition, repeating this
3 procedure for different data partitioning reduces sampling variability and allows for
4 the determination of the precision of the performance estimator (see section 5.3 for
5 details).

6 **3. ... In line 15 the authors mentioned about uncertainties and ways to communicate**
7 **them. This is very important but I can not see how this document assists on this, neither in**
8 **the methodology nor inside the manuscript. The authors should be quite clear in showing**
9 **how they tackle this problem.**

10 This referee comment clearly shows us a need for further clarification in the revised
11 manuscript. We disagree that the communication of uncertainties is not part of our study.
12 However, we acknowledge, that we only presented one possible form of communication, the
13 visualization of (specific) uncertainties, which is also recommended in literature in the
14 context of risk and uncertainty assessment. Information on uncertainties might be easier
15 understood by the stakeholders if they are visualized (Kunz et al., 2011). Accordingly, we
16 propose to enhance the communication with stakeholders about model uncertainties by
17 presenting the possible overlaps of susceptibility classes taking into account the confidence
18 limits of the model predictions in several maps (refer to Figure 6 in the original manuscript).
19 This analysis and visualization is one of our main points in our study. The general concept of
20 the need for communication and visualization is discussed in section 7 of the revised
21 manuscript. This connection of the analysis of the prediction uncertainties and their
22 visualization as first step towards communication was more emphasized at different sections
23 of the revised manuscript as indicated below. The methodology of the analysis of the spatially
24 varying prediction uncertainties was presented in section 5.5. Accordingly the results were
25 presented in section 6.4 in the refereed manuscript. We included more about the
26 communication in the discussion (section 7.3) of the revised manuscript, to draw attention to
27 more the potential of communicating effects of uncertainties to stakeholders by providing
28 illustrative maps (as shown in a further comment).

29 Generally, section 2 can be seen as an extension of the introduction which was introduced in
30 order to keep the introduction shorter. This section was altered substantially in the revised
31 manuscript as further replies on referee comments will show.

1 Added to page 1004, line 15

2 Since the application of the landslide susceptibility map resulting from this study is
3 planned for implementation by municipal authorities, our main focus is to identify
4 different aspects of quality (depending on input data, model performance and provided
5 analysis of uncertainties). Accordingly, the purpose of this study is to review the
6 characteristics that describe quality, to analyse the (statistical) model quality and to
7 assess and visualize the uncertainty of the prediction.

8 Added to page 1004, line 24

9 This very broad term of quality can be interpreted in several ways and on several
10 stages of the process of preparing a landslide susceptibility map as described, amongst
11 others, by Carrara (1993), Carrara et al. (1995), Ardizzone et al. (2002), Guzzetti et al.
12 (2006). In general, a good quality refers to input data, model or result (e.g.
13 susceptibility map) which includes relatively low uncertainties.

14 Added to page 1006, line 15

15 **2.3 Quality of final susceptibility map**

16 One important model form uncertainty which can be visualized in a map is the
17 prediction uncertainty arising from using a statistical model. The output of a statistical
18 model for spatial modelling is usually comprised of a single probability value for each
19 unit of the prediction surface (grid cells, slopes or terrain units). These individual
20 probability values represent an estimated conditional mean value of the predicted
21 probability (Hosmer and Lemeshow, 2000). Therefore, there is a prediction
22 uncertainty or possible range, as determined by the standard error of the predicted
23 probabilities, of probability estimates for each unit of the susceptibility map (Guzzetti
24 et al., 2006). Estimating the standard error was analysed and presented in previous
25 research (e.g. Guzzetti et al., 2006; Van Den Eeckhaut et al., 2009a; Rossi et al., 2010;
26 Sterlacchini et al., 2011). However, the way it affects the appearance of the classified
27 landslide susceptibility map is of interest for planning purposes as considering these
28 prediction uncertainties might result in overlaps of different susceptibility classes.
29 Naturally, the amount of overlapping raster cells and therefore the uncertainty in the
30 final classified map might be dependent on the number of classes and the selected
31 thresholds for the classification. However, the analysis of the standard error of the

1 predicted probabilities and the prediction uncertainty analysis are independent of any
2 class thresholds.

3 **4. P1004 line 26: I suggest rephrasing this sentence and to be more specific regarding**
4 **the terms of quality and its analysis.**

5 We thankfully included the suggested rephrasing in the revised manuscript. This sentence was
6 moved to the introduction of the manuscript. There the aspects of quality analysed within this
7 study (depending on input data, model performance and provided analysis of prediction
8 uncertainties) were pointed out more specifically. Furthermore, these terms were better
9 described in section 2 of the revised manuscript. Please see the added text to page 1004, line
10 15 presented in our reply on comment number 3.

11 **5. P1005 line 5 – 8: I disagree with this statement. In fact, I suggest that the authors**
12 **rephrase the complete paragraph. The idea of making a susceptibility map which can lead**
13 **to a risk assessment (quantitative) is to assess the uncertainties that are either inherent or**
14 **non inherent. There are ways and procedures to assess these uncertainties and quantify**
15 **them. The authors should carefully look into this.**

16 This is an important point which was considered together with the next comment while
17 revising the section 2 of the manuscript. Analysing epistemic and aleatory uncertainties is a
18 challenging topic in all fields that use some sort of model (e.g. risk assessment, computation
19 science or ecology (Elith et al., 2002; Roy and Oberkampf, 2011; Hill et al., 2013)). Therein
20 the quantification of aleatory uncertainties is quite common to be assessed with a probabilistic
21 approach. However, considering epistemic uncertainties in a quantitative manner is more
22 challenging (Oberkampf et al., 2004; Roy and Oberkampf, 2011).

23 In the revised manuscript we first defined quality related to uncertainty. Secondly we defined
24 the different types of uncertainty (aleatory and epistemic) according to literature. Finally we
25 added some more details on the specific uncertainties occurring in statistical modelling to
26 each type of quality we identified. For these edits please see our reply to the next comment.
27 The details of our changes in the revised manuscript are presented in the following:

28 Added to page 1004, line 24

29 This very broad term of quality can be interpreted in several ways and on several
30 stages of the process of preparing a landslide susceptibility map as described, amongst

1 others, by Carrara (1993), Carrara et al. (1995), Ardizzone et al. (2002), and Guzzetti
2 et al. (2006). In general, good quality refers to input data, model or result (e.g.
3 susceptibility map) which includes relatively low uncertainties.

4 Landslide susceptibility modelling is inherently riddled with uncertainties. In
5 engineering and risk assessment a basic distinction between aleatory and epistemic
6 uncertainties is very common (Hill et al., 2013; Hoffman and Hammonds, 1994;
7 Oberkampf et al., 2004; Roy and Oberkampf, 2011). Many processes and conditions
8 leading to landslide occurrence are known and mappable, known but not collectable,
9 or are simply unknown (Carrara et al., 1999). The imperfect understanding of the
10 complexity of this hazardous phenomenon arising from the missing knowledge
11 (Ardizzone et al., 2002; Kunz et al., 2011) is generally referred to as epistemic
12 uncertainty (Hoffman and Hammonds, 1994; Hora, 1996; Oberkampf et al., 2004).
13 Epistemic uncertainty is often divided into input uncertainty, parametric uncertainty
14 and structural or model form uncertainty (Roy and Oberkampf, 2011; Rougier and
15 Beven, 2013). Naturally, these uncertainties can be reduced by improving knowledge
16 of the subject (Spiegelhalter and Riesch, 2011). Unavoidable uncertainty arising from
17 the natural variability and/or randomness of the natural hazard process can be
18 distinguished as aleatory uncertainty (Rougier and Beven, 2013; Rougier, 2013).
19 Although these distinctions can be applied, the organization of uncertainties is
20 dependent on the study objectives (Hora, 1996; Roy and Oberkampf, 2011).

21 In the following, we will discuss quality by addressing uncertainty issues regarding
22 input data (parametric uncertainty), model performance (model form uncertainty) and
23 the final susceptibility map associated with statistical modelling. Details on other types
24 of uncertainties which might be more important for other types of susceptibility
25 assessment (e.g. deterministic) or on the propagation of uncertainties can be found
26 amongst others in Hoffman and Hammonds (1994), Draper (1995), Helton et al.
27 (2010), Karam (2005), Oberkampf et al. (2004), Rougier (2013).

28 Added to page 1005, line 25

29 The quantitative incorporation of parametric uncertainty in subsequent hazard and risk
30 assessment is still a challenge (Ardizzone et al., 2002; Oberkampf et al., 2004; Roy
31 and Oberkampf, 2011).

1 **6. P1005 and P1006: It is a nice effort to try to summarize the aspects that can**
2 **influence the quality of a susceptibility maps. But at the same time, I would suggest**
3 **including the uncertainties derived from them and divide them in epistemic and aleatory.**

4 We would like to thank the referee for suggesting us to include a classification of the
5 proposed aspects of quality by the uncertainties (epistemic and aleatory) that are influencing
6 the quality. The classification of uncertainty types was presented in the previous comment
7 number 5. Accordingly, we adapted the description of the types of quality, adding some
8 considerations on the present type of uncertainty:

9 Added to page 1005, line 14

10 **2.1 Quality of input data**

11 Achieving a good quality of the final landslide susceptibility map starts with the
12 quality of the input data set for the modelling. Besides the geomorphological
13 relevance, the spatial resolution and accuracy of the geo-environmental as well as the
14 landslide inventory data is important (Van Westen et al., 2008). During the preparation
15 of all input data (done by mapping or measuring) subjectivity, the experience of the
16 mapper, measuring errors or imprecision in computer processes are sources of
17 parametric uncertainty (Mosleh, 1986; Ardizzone et al., 2002; Elith et al., 2002; van
18 Westen et al., 2005, 2008).

19 Added to page 1005, line 21

20 This source of epistemic uncertainty can rarely be reduced and other assessments of
21 the uncertainty have to be selected. Therefore, estimation on the completeness of the
22 landslide inventory and details on the collecting and mapping method giving
23 information on the accuracy and the location of the landslide point/line/polygon (main
24 scarp or entire landslide body) are very important. This influences the further usage of
25 the input data set and the feasible interpretation of the susceptibility maps
26 substantially. The explicit incorporation of parametric uncertainty in subsequent
27 hazard and risk assessment is still a challenge (Ardizzone et al., 2002; Oberkampff et
28 al., 2004).

29 Added to page 1005, line 27

30 **2.2 Quality of statistical models**

1 Every model is a simplification of reality. Therefore, while modelling landslide
2 susceptibility, it should be expected that some discrepancies regarding the ability to
3 explain all the processes involved in the phenomenon would naturally occur (Rougiér
4 and Beven, 2013). Every modelling result is highly dependent on the input data, the
5 assumptions made to set up the model design and the selection and performance of an
6 appropriate model. These assumptions also define the limitations of the model, its
7 result and the allowed interpretation of it. Quantifying this part of the model form
8 uncertainty is challenging. However, model validation procedures have been
9 developed and are commonly applied to assess the model performance and therefore
10 the model form uncertainty (Roy and Oberkamp, 2011).

11 The prediction skills (Guzzetti et al., 2006) can be analysed quantitatively with
12 various performance measures and estimation techniques, and qualitatively by
13 considering expert knowledge of a particular study area. Qualitative methods analyse
14 the geomorphic plausibility of the map (Bell, 2007; Demoulin and Chung, 2007).
15 Common quantitative performance measures are success/prediction rate (Chung and
16 Fabbri, 2003, 2008), confusion matrix or error rates (Brenning, 2005; Beguería,
17 2006b), and cost curves (Frattini et al., 2010). Among the performance estimation
18 techniques and measures, cross-validation using a single hold-out method and the area
19 under receiver operating characteristic curve (AUROC) value based on ROC plots
20 (Beguería, 2006; Brenning, 2005; Frattini et al., 2010) are usually applied (i.e. Chung
21 and Fabbri, 2003, 1999; Fabbri et al., 2003; Remondo et al., 2003; Brenning, 2005;
22 Beguería, 2006; Frattini et al., 2010; Rossi et al., 2010).

23 In single hold-out methods the data set is split in one single training and test sample.
24 The training sample is used to fit the model and the test sample is used to determine
25 the model performance. This results in a single estimate of the performance measure
26 (e.g. one single AUROC value) without providing a measure of precision of the
27 estimator. The estimate depends on the (random) sample used for modelling the
28 susceptibility and testing the model's performance, which may itself have "peculiar"
29 random characteristics that would be different for a different test set. Repeated k-fold
30 cross-validation solves this problem by using, one after another, different subsets or
31 partitions of the data set as test and training sets, thus effectively using the entire data
32 set for performance estimation (Brenning, 2012a, 2012b). In addition, repeating this

1 procedure for different data partitioning reduces sampling variability and allows for
2 the determination of the precision of the performance estimator (see section 5.3 for
3 details).

4 Depending on the partitioning method (randomly or spatially) to obtain the folds these
5 statistical estimation methods can further provide a means for assessing the non-spatial
6 transferability of a model onto a different, independent random sample, and the spatial
7 transferability into a spatially separate area. Spatial transferability refers to the
8 capability of the model to generalize empirical relationships learned on a training data
9 set, and to transfer these relationships to (usually adjacent) regions without major loss
10 in predictive performance (Brenning, 2005; von Ruetten et al., 2011).

11 Additionally, aleatory uncertainties are of importance in the modelling stage, as even
12 if all parameters would be known perfectly some deviance (or discrepancy) of the
13 model results to the nature might still occur due to the natural variability of the process
14 (Elith et al., 2002, Rougier and Beven, 2013).

15 Added to page 1006, line 15

16 **2.3 Quality of final susceptibility map**

17 One important model form uncertainty which can be visualized in a map is the
18 prediction uncertainty arising from using a statistical model. The output of a statistical
19 model for spatial modelling is usually comprised of a single probability value for each
20 unit of the prediction surface (grid cells, slopes or terrain units). These individual
21 probability values represent an estimated conditional mean value of the predicted
22 probability (Hosmer and Lemeshow, 2000). Therefore, there is a prediction
23 uncertainty or possible range, as determined by the standard error of the predicted
24 probabilities, of probability estimates for each unit of the susceptibility map (Guzzetti
25 et al., 2006). Estimating the standard error was analysed and presented in previous
26 research (e.g. Guzzetti et al., 2006; Van den Eeckhaut et al., 2009; Rossi et al., 2010;
27 Sterlacchini et al., 2011). However, the way it affects the appearance of the classified
28 landslide susceptibility map is of interest for planning purposes as considering these
29 prediction uncertainties might result in overlaps of different susceptibility classes.
30 Naturally, the amount of overlapping raster cells and therefore the uncertainty in the
31 final classified map might be dependent on the number of classes and the selected
32 thresholds for the classification. However, the analysis of the standard error of the

1 predicted probabilities and the prediction uncertainty analysis are independent of any
2 class thresholds.

3 **7. P1005 and P1006: In the course of the manuscript the term “susceptibility map” is**
4 **very general. The authors assume that these types of assessments are done in a regional**
5 **scale with a statistical approach. This is not the case in reality. I suggest that the authors**
6 **make a clear definition of the type of susceptibility map they are analysing ...**

7 In the introduction a description of the different methods of preparing a landslide
8 susceptibility map was included in the revised version (after Soeters and Van Westen, 1996;
9 Fell et al., 2008). Fell et al. (2008) listed the best suitable scale with the respective methods.
10 We emphasize the choice of the method according to the aimed map output scale of 1:25,000
11 and the list given by Fell et al., (2008). For more details and the changed text in the revised
12 version please also refer to the answer on the referees’ comment 1 on P1003 line 20-25.

13 **8. ... and if their proposed method can be applied to any other type of susceptibility**
14 **maps.**

15 This is a very interesting field, and we understand, that this would fit good in our discussion
16 of the different types of quality and uncertainty. However, the analysis of the possible
17 application of the proposed methods to other types of susceptibility mapping (heuristic or
18 deterministic) was not the focus of this study/review. We added text to point this out to avoid
19 misunderstandings.

20 For the added text please see our reply to the comment 5 on P1005 line 5 – 8. The text stating
21 that our considerations on the quality are mainly focused on statistical modeling was added
22 there (page 1004, line 24). Furthermore, we changed the title of section 2 to be more specific
23 “Considerations on the quality of statistical landslide susceptibility models and resultant
24 maps”.

25 Nevertheless, we want to give some general comments on the applicability to other types of
26 susceptibility maps/models in this context. Assessing the model performance with
27 independent test sets is recommended for any susceptibility assessment method. This is
28 important in science but also for the stakeholders to know how good the model fits to the
29 landslides that occurred in the past, assuming that the triggering and predisposing conditions
30 have not changed significantly since. As the heuristic and deterministic methods are less

1 reliant on the landslide inventory at the stage of modelling the susceptibility, these methods
2 are less dependent on the selection of landslide samples. However, in the assessment of the
3 model performance, the selection of the landslide sample might have a clear effect on the
4 performance measure. This could be assessed in a similar manner as the k -fold cross-
5 validation. The visualization of the prediction uncertainty might be transferred to any
6 statistical method which provides the possibility of calculating confidence intervals. This
7 method very specifically relates to the usage of a statistical model. However, this
8 methodology might inspire the assessment and visualization of uncertainties e.g. of assigning
9 different weights in heuristic susceptibility mapping, or different calibration of factors in a
10 deterministic assessment in a similar manner.

11 **9. *P1005 line 27: I suggest changing the subtitle “Quality of the statistical model”. It is***
12 ***not the quality of the models that should be the focus in this section (since they have been***
13 ***applied soundly in many other cases) but how the performance of the models and its***
14 ***applicability to landslide cases. This performance should be linked to the quality of the data***
15 ***and the uncertainties from the application.***

16 The authors are thankful for the suggestion of changing the subtitle. In order to be consistent
17 with the other subtitles in this section we changed the subtitle to “Quality of statistical model
18 form”. The model form uncertainty can be assessed with model performance measures. The
19 model performance is amongst other influences dependent on the selected sample, the sample
20 size and also on the resolution or scale of the input data. Whereas the effects of a changing
21 sample and sample size (quality or completeness of the inventory) are addressed in the study,
22 the analysis of the link of the performance to the quality of the data (resolution, scale) was
23 beyond the scope of this study.

24 **10. *P1006 line 15: This statement should be referenced or if not explained thoroughly.***
25 ***For this reason, it is suggested to define the uncertainties involved in the mapping and to***
26 ***classify them. Once this is done, it can be referred to this classification.***

27 We are thankful for pointing out a need for clarification. We altered this section to be more
28 specific regarding the types of uncertainties which can be analysed to define the quality of the
29 susceptibility map itself better.

1 For the changes in the text please refer to the additions done to page 1006, line 15 described
2 in the reply to the comment number 6.

3 ***11. P1006 line 26 – 28: I suggest rephrasing the sentence. This is dependent on the***
4 ***amount of susceptibility classes and the choice of classification.***

5 The authors are thankful for the suggestion of rephrasing the sentence. We agree with that
6 comment. The possible overlaps of susceptibility classes are strongly related to the number of
7 classes and selected thresholds. We rephrased the sentence and added some new sentences in
8 the revised version.

9 For the edits please refer to our reply to comment 6 and the changes added to page 1006, line
10 15

11 ***12. P1007 line 1 -13: The authors attempt to mention the quality achieved by***
12 ***communication and presentation of the uncertainties. However, the paragraph is very poor***
13 ***and does not present something valuable for the manuscript. This is a very complex issue***
14 ***that the authors should discuss in more detail (if not, this should be removed or added to***
15 ***other section).***

16 This section was altered and moved to the discussion of the spatially varying prediction
17 uncertainties in the discussion section of the revised manuscript. In the discussion section we
18 use the statements from literature to underpin the benefit of analysing the spatially varying
19 prediction uncertainties and to visualize them. Generally the discussion section 7.3 was
20 changed substantially. Therefore, we present the new text here:

21 Added to page 1029, line 25

22 Some model form uncertainties within this method arise from using the lookup table
23 for transferring the prediction standard error to all grid cells as shown by the range of
24 resulting R^2 . This method might be improved or substituted by a function assigning the
25 standard errors to all grid cells.

26 It was found that in the classified map the majority of grid cells did not change.
27 However, there are differences between the modelling domains where some domains
28 had larger overlaps of different susceptibility classes than others. Special attention

1 should be given to the low susceptibility class. Here, the highest percentage of
2 overlapping classes and underestimation of the susceptibility were detected.

3 The visualization of these spatially varying uncertainties is of special interest for
4 future land-use and development planning usually performed by non-landslide experts.
5 In the aftermath of this study each landslide susceptibility class will be related to, not
6 legally binding, recommendations for the designation of new building areas.
7 Therefore, a misclassification (e.g. low instead of medium susceptibility) might lead to
8 an interpretation by the municipality or landowner that underestimated landslide
9 susceptibility. Knowledge about the susceptibility class overlaps might outline where
10 more caution and detailed investigations are necessary. Additionally, it also shows
11 where no uncertainties are expected, which might help to avoid costs for slope
12 investigations.

13 There is also a need to communicate the research results and their quality with
14 appropriate explanations for the local officials, environmental managers and the public
15 to raise awareness and knowledge on it which leads to an easier understanding and
16 incorporation of the results into the decision-making process (Brierley, 2009; Hill et
17 al., 2013; Knuepfer and Petersen, 2002; Rogers, 2006). This analysis might aid to a
18 good acceptance of the landslide susceptibility maps in the local governments, as
19 instead of a fuzzy statement on involved uncertainties these are clearly shown in a map
20 on grid cell level (Guzzetti et al., 2006; Luoto et al., 2010). Furthermore, the
21 preparation of the susceptibility maps showing the class overlaps contributes to an
22 easier understanding of the possible effects of the prediction uncertainties.

23 The question if the policy makers or stakeholders are really interested in knowing
24 more about the uncertainty is discussed conversely. The study of Brugnach et al.
25 (2006) pointed out that the confidence in modelling results is dependent on the way
26 the uncertainties are addressed. Policy makers were missing more information on the
27 uncertainty of any model result. Therefore, the modelling results should be presented
28 with a measure of uncertainty or confidence indicator (Brugnach et al., 2006). In
29 habitat suitability modelling the visualisation of uncertainty was identified as relevant
30 to inform decision-makers about areas with extreme error, but also about areas which
31 are particularly well modelled (Elith et al., 2002). This openly addresses the
32 uncertainties involved in the maps instead of giving an impression of certainty (Elith

1 et al, 2002). However, interviews of Klimeš and Blahůt (2012) showed that local
2 governments do not want any information on uncertainties.

3 Nevertheless, these uncertainties might have severe consequences on buildings and
4 their inhabitants if an event occurred within the uncertainties of the method used to
5 delineate the hazard zones. The converse discussion shows, that more or better
6 communication with the stakeholders or policy makers (also during the modelling
7 process) is necessary to learn about uncertainties and enlarge confidence into the
8 modelling (Brugnach et al., 2006). However, the way how the uncertainties are
9 presented to the stakeholder has to be adapted by the scientist to ensure the success of
10 the communication. The visualization of some aspects of the quality of landslide
11 susceptibility maps, such as the spatially varying prediction uncertainty, can enhance
12 the communication among experts and decision-makers to facilitate informed
13 decisions (Kunz et al., 2011).

14 Additionally, further aspects of considering and communicating the effects of
15 epistemic uncertainty are still open research fields in susceptibility modelling. A clear
16 assessment of these is necessary to evaluate on their consequences on the
17 susceptibility (or hazard or risk) map.

18 ***13. P1007 Title section 3: The subtitle is very generic and does not portray the area as***
19 ***such. Many places in the world are heterogeneous too. Is this heterogeneity based only on***
20 ***the lithological factors? Then this should be included and a more concise title is suggested.***

21 In the revised manuscript a new subtitle for section 3 will be included: “Lower Austria
22 landslide occurrence”.

23 ***14. P1007 section 3: The authors should include a map and a table regarding the***
24 ***inventory. This will help the reader to understand the attributes and the spatial distribution***
25 ***of the inventory in the heterogeneous area.***

26 We understand the interest on more details on the inventory. However, the landslide
27 distribution is presented in Table 1. The table shows the total number of landslides and also
28 the landslide density. This is a function of number of landslides per km² and is very different
29 for each lithological unit. A figure of the landslide inventory of the entire study area was
30 presented in Glade et al. (2012) and will be published in a general paper about the landslide

1 inventory mapping on the basis of a high resolution LiDAR DTM (Petschko et al.,2013a).
2 Considering the length and amount of figures we already have in this manuscript we prefer to
3 not publish another inventory map here. According to the referee comment we consider that
4 the form of the inventory is quite unclear to the reader. Therefore, we included some more
5 text to describe the nature of the landslide inventory better.

6 Added to page 1008, line 15

7 While rock fall and debris flows typically occur in the southern lithology
8 (Austroalpine Unit), earth and debris slides occur all over the province with different
9 densities (Tab. 1), sizes and depths. Only earth and debris slides which were mapped
10 with one point in the main scarp of each slide were within the scope of this study;
11 recent examples of these landslide types are shown in Fig. 2.

12 Added to page 1009, line 24

13 However, no attributes (landslide type, estimated age, landcover, time/date of
14 occurrence etc.) were assigned to each point.

15 ***15. P1007 line 27: The authors should explain why and what is the importance of***
16 ***featuring the median slope angle. What influence this have in the result and what is the***
17 ***significance of this value in a scale like this?***

18 We are thankful for outlining the possible source of misunderstanding in this line. The median
19 slope angle is purely used as a proxy to describe the differences in the topography in the
20 different lithological units of the study area. We used this simple parameter, as it shows which
21 units are rather flat, or which units are rather steep. An impression we wanted to give the
22 reader to understand the heterogeneity of the study area better. Therefore, we also supplied
23 Figure 2 which shows landslides in all the different settings of lithology but also topography.
24 The text in the revised manuscript was changed accordingly:

25 Added to page 1008, line 1

26 The median slope angle was used as a simple proxy of the topographic characteristics
27 to highlight the diverse conditions across Lower Austria. The median slope angle
28 ranges from a minimum of $<1^\circ$ (alluvial deposits) to a maximum of 27° (Austroalpine
29 Unit with dolostone; Tab.1).

1 ***16. P1008 line 4: Land use as mentioned in the manuscript differs among topography***
2 ***and lithology. Why not consider this factor? The authors mention the temporal aspect of***
3 ***land use, but this is not an excuse to exclude this of the analysis. Besides this, land use has***
4 ***a very important influence in the infiltration process. Why instead of using proxies for***
5 ***infiltration, not link the land use to these factors too? I suggest that the authors make their***
6 ***assumptions understandable regarding this and make a clear reasoning about this.***

7 We agree that land cover has an important influence on the infiltration and evaporation
8 processes which are important for the slope stability (Crozier, 1986). A close relationship
9 between land cover and the occurrence of landslides can usually be found by the analysis of
10 event landslide inventories. These inventories are collected right after an event; therefore the
11 landslides correspond to the recent land cover conditions. It is more straight forward to use an
12 event landslide inventory with the respective land cover information than to use an inventory
13 mapped on LiDAR data, as the absolute age of the landslides is unknown (van Westen et al.,
14 2005). Some of the mapped landslides might be very old (much older than 100 years) and
15 some dynamic triggering conditions (e.g. land cover, rainfall) are not traceable over the entire
16 study area anymore. Therefore, we decided to prepare a landslide susceptibility map on the
17 basis of the rather static local terrain conditions only (Brabb, 1984; Soeters and Van Westen,
18 1996).

19 Land use or land cover changes are documented since the medieval but occurred also more
20 recently throughout the province. Studies in Lower Austria (the municipality of Ybbsitz and
21 in the Vienna Forest) have shown that land cover changes have occurred with different extent
22 in the past (Fritz, 2005; Johann, 2005; Lettner and Wrбка, 2011). These are very different in
23 the West of the province (Ybbsitz) from the East of the province (Vienna Forest). In Ybbsitz
24 arable fields mainly were converted to meadows and pasture and there was also an increase in
25 forest during 1822 to 2006 (Lettner and Wrбка, 2011). Furthermore, the influence of the
26 ironware industry was large in this area from late mediaeval times to the mid- 19th century
27 (Lettner and Wrбка, 2011). The consequence was a widespread deforestation in this area
28 (Lettner and Wrбка, 2011). In the Vienna Forest deforestation occurred due to the need of fire
29 wood in the city of Vienna (Johann, 2005) and due to the expansion of settlements (Fritz,
30 2005). However, in the 20th century further deforestation was tamed to preserve the forest. In
31 recent years the main observed land cover change in the Vienna Forest is from meadow to
32 settlement area as the vicinity to Vienna attracted many new inhabitants (Fritz, 2005).

1 The influence of the landscape history and extent e.g. of the transition from forest to pasture
2 and from pasture to forest again on the slope stability (or infiltration capacity) compared to a
3 slope which was forested all the time is unknown in the study area. Van den Eeckhaut et al.
4 ((Van Den Eeckhaut et al., 2009b)2009) showed that landslides repeatedly re-activate under
5 forest. Whereas it is assumed that reforestation and the regrowth of roots will increase the root
6 cohesion and evaporation and increase the slope stability (Markart et al., 2006; Bathurst et al.,
7 2010). However, a study from the Flysch in the Spanish Pyrenees showed, that landslides still
8 occurred in arable fields re-vegetated by shrubs or trees (Beguería, 2006a). This shows very
9 contradictory experiences from the field and from modelling concerning the effect of land
10 cover or land use on landslide activity, which shows the need for further research in the study
11 area (Papathoma-Köhle and Glade, 2013). Furthermore, the time span how long such changes
12 (like deforestation) are influencing the slope even after reforestation are not well understood
13 and more research is necessary.

14 This relevant data on land cover changes of the past and their influence on the slope stability
15 in Lower Austria are not available for the entire study area. We conclude using the recent land
16 cover in the modelling might introduce an unwanted bias into the model, as this data does not
17 portray dynamics in past land cover changes. For more considerations on this topic we would
18 like to refer to a publication planned at the 3rd World landslide forum in Beijing 2014
19 (Petschko et al., 2013b).

20 We included some more text to make our decision better traceable for the reader. Considering
21 the general length of the manuscript and the focus of the study we provide a reference in the
22 text to our further research for more detailed information. The section 4.2 was restructured,
23 therefore the new reference (to page and line) might be confusing in comparison with the
24 original manuscript. Therefore we inserted the entire paragraph on land cover here:

25 Added to page 1011, line 27

26 Land cover data for Lower Austria was also available for this study, but was not
27 included in the analysis. Since the ages of the landslides were not available in the
28 inventory, it would not be accurate to associate the landslide distribution with present
29 land cover conditions (Petschko et al., 2013b). We simply do not know how land
30 cover had historically changed and influenced all of the landslides in this inventory,
31 which is important to understand the changing conditions of slope stability. (Glade,
32 2003; Beguería, 2006a; Van Den Eeckhaut et al., 2009b; Bathurst et al., 2010). For

1 example, areas which are forested today, might not have been forested for a long time
2 period in the past, e.g. due to influences of mining ore in the study area (Lettner and
3 Wrbka, 2011). Therefore, the landslide susceptibility models were prepared focussing
4 on local terrain conditions (Brabb, 1984), which are relatively static compared to the
5 dynamic nature of land cover.

6 **17. P1008 line 17: The choice of earth and debris slides is clear and the authors try to**
7 **include hydrological factors inside the analysis which is a good point. However, one of the**
8 **main triggers of this type of slides is the intensity-duration of the rainfall. How is this taken**
9 **into account in this analysis?**

10 We are thankful for the positive feedback on including factors such as the topographic
11 wetness index in our modelling. The point on considering precipitation in the model is rather
12 challenging considering that the exact triggering conditions of the mapped landslides in the
13 inventory are unknown. Usually convective storms or long lasting rainfall events increase the
14 wetness of the slope and decrease the slope stability. However, reliable rainfall data available
15 in Lower Austria only dates back to 1970 which might only cover a small part of all the
16 triggered landslides (see also the previous comment regarding the potential age of the
17 landslides in the inventory). Furthermore, it is questionable if the mean or max rainfall
18 amount in this time span is an appropriate parameter to be used in the modelling. Therefore,
19 we decided to leave out all dynamic factors in the analysis of the landslide susceptibility.
20 Including different precipitation data in the statistical susceptibility model was beyond the
21 scope of the presented study but surely is an interesting field of research. In the text we
22 pointed out the type of susceptibility map more clearly.

23 For the added text please see our reply to comment 16 with the text added to page 1011, line
24 27.

25 **18. P1009 line 10-12: It is not clear why the authors had a LIDAR data with a**
26 **resolution of 1x1, they resample it to have a final resolution of 10x10. I am certain that this**
27 **loss of resolution will affect the slopes and derivatives factors. What type of resampling was**
28 **done?**

29 We agree with the reviewer on the importance of stating the resampling method as this might
30 change the data significantly. In this study we used bilinear interpolation to resample the

1 DTM from 1 m x 1 m resolution to 10 m x 10m resolution. All the derivatives were calculated
2 from the DTM grid with 10 m x 10 m cell size. We are aware, that this resampling to a lower
3 resolution affects the data and all the derivatives. However, we argue according to Van
4 Westen et al. (2008) that using input variables with a very high resolution might have adverse
5 effects on the final susceptibility map. The local variations captured in the LiDAR DTM in
6 combination with the positioning of the point while mapping or randomly sampling the
7 landslide point might not describe the more general slope conditions of landslide occurrence
8 (Van Westen et al., 2008). However, we want to point out that analyzing the influence of
9 input data resolution was beyond the scope of this study. Accordingly some more details were
10 added in the text of the revised manuscript:

11 Added to page 1009, line 9

12 Considering the detailed resolution we have given in the ALS-DTM and the rather
13 coarse resolution given in the soil data (50 m x 50 m) we had to find a compromise for
14 the analysis and output of the susceptibility map. We decided an output resolution of
15 the maps of 10 m x 10 m would be suitable to produce 1:25.000 scale maps; we are
16 still able to take advantage of the high resolution of the topographic data but also
17 avoid wrong signals in the modelling form very local variations in the derivatives of
18 the high resolution DTM (Van Westen et al., 2008). Although, the exploratory
19 variables were resampled by bilinear interpolation to a 10 m x 10 m resolution for
20 modelling purposes, we are aware that this artificial improvement of the data
21 resolution does not increase the data accuracy.

22 ***19. P1009 4.1 Response variable: Choosing to work with a point inventory has a great***
23 ***influence on the final susceptibility map results, mostly when assessing fast moving***
24 ***landslides like debris flows. I disagree with the authors that there are small differences***
25 ***when choosing the main scarp or the entire landslide, this is a clear problem of scale***
26 ***(check also reference listed). The authors should dig into this deeper and come with the***
27 ***right assumption for using a point inventory. ...***

28 We would like to thank the referee for pointing out some need for a more precise description
29 of the assumptions and previous research done on the selection of points in the main scarp
30 instead of using randomly selected points in the entire landslide polygon. We have to mention
31 that we did not model debris flows as we modelled earth and debris slide susceptibility.

1 However, we agree that the effect on the susceptibility map is high if showing the probability
2 values only. Precisely the entire interpretation of the map changes if only points from the
3 main scarp are used within the modelling. However, what we analysed in the previous study
4 and wanted to point out here is the difference in the final classified susceptibility map (in 3
5 classes) using points randomly selected in the main scarp or in the entire body of the
6 landslide. The random selection of multiple points/grid cells or one point/grid cell only per
7 each landslide is a procedure usually done in modelling (e.g. Atkinson et al., 1998; Beguería,
8 2006b; Van Den Eeckhaut et al., 2006; Felicísimo et al., 2012; Schicker and Moon, 2012).
9 This is done because of considerations on avoiding spatial autocorrelation (Van Den Eeckhaut
10 et al., 2006; Guns and Vanacker, 2012). Our results showed a comparable high model
11 performance using either one point in the entire body, or one point in the main scarp of the
12 landslide. Furthermore, the classified susceptibility map changed only marginally (Petschko et
13 al., 2013c). Considering the need for mapping landslides in the entire province and restricted
14 resources available, we decided on mapping the main scarp of landslides with one point only
15 in the remaining study area (Petschko et al., 2013c). In this application of the inventory for
16 deriving a classified susceptibility map with three classes we conclude that the usage of the
17 point inventory is reasonable. Accordingly some text was added in the revised manuscript.

18 Added to page 1009, line 24

19 Considering the large study area and the aimed result of a susceptibility map with
20 three classes a point inventory was preferred over a polygon inventory (Petschko et al,
21 2013c). The decision to map one point per landslide was aimed at increasing mapping
22 efficiency, avoiding uncertainty related to mapping landslide polygon boundaries,
23 reducing spatial autocorrelation of the case samples (e.g., landslides) and providing
24 equal treatment of small and large landslide samples (Carrara et al., 1991; Atkinson et
25 al., 1998; Van Den Eeckhaut et al., 2006; Heckmann et al., 2013; Petschko et al.,
26 2013a). A comparison of sampling with either a single point for the main scarp or a
27 random point anywhere in a landslide polygon was conducted by Petschko et al.
28 (2013c). They observed only small differences between the predictive model
29 performances and classified susceptibility maps for the two landslide sampling
30 schemes.

1 **20. ... Another difficulty regarding this is the slide mechanism and its retrogressive**
2 **failure. Is the point inventory enough then?**

3 A statistical model itself is always a snapshot in time and can not include retrogressive failure.
4 The statistical model takes into account what has happened so far. Different approaches of
5 sampling landslide information are available including the identification of the pre-hillslope
6 gradient (Atkinson and Massari, 1998; Van den Eeckhaut et al., 2006), focus on the main
7 scarp only (Begueria, 2006b; Van den Eeckhaut et al., 2006) or on the area upslope from the
8 main scarp (Suzen and Doyuran, 2004; Yesilnacar and Topal, 2005). However, the process
9 and extent of retrogressive failure is very depending on the local slope conditions
10 (hydrological and soil mechanical processes, soil thickness, material, etc.). Therefore, it
11 would be necessary to know the location and magnitude of an occurring landslide to analyse
12 this with a deterministic or physical slope stability model. Concluding, it is not a matter of
13 which type of inventory is used in the analysis (point or polygon) but rather a question of the
14 selection of models and the scale of the analysis if a retrogressive failure can be taken into
15 account.

16 Considering the general length of the manuscript no text was added regarding this comment.

17 **21. P1010 4.2 Explanatory variables: How is it taken into account a debris flow that**
18 **happens several times in the same channel?**

19 In this study only the susceptibility of debris slides and earth slides was analyzed, not of
20 debris flows. Issues of reactivation or of magnitude or frequency were not in the focus of this
21 study. No changes made.

22 **22. P1011 line 8: Infiltration and run-off are closely related to land use also. Why only**
23 **use the lithological factors? Is this accurate enough?**

24 We agree with the comment of the referee that infiltration and run-off are closely related to
25 land use. However, we want to point out that we did not directly use the lithological map in
26 the modelling. We used the lithology to split the study area into more homogeneous zones,
27 which allow for a better characterisation of the area with separate susceptibility models. This
28 partition of the study area resulted in a better representation of the predisposing and
29 preparatory factors of landslides in each unit. Applying this partitioning results in a more

1 accurate susceptibility map compared to a basic approach. Regarding the land use parameter
2 see reply to comment 16.

3 **23. P1011 line 15-28: Is this relevant for debris flows? How do the tectonic arrange**
4 **ffects this flows in reality? Mention some references regarding this.**

5 We would like to point out that this study is dealing with debris and earth slides and not with
6 debris flows. The influence of the presence of tectonic fault lines and nappe boundaries on
7 earth and debris slides was described on page 1011 in the paragraph from line 14 to line 24 in
8 the original manuscript. References on the possible influence of fault lines on landslides
9 (Crozier, 1986) and of nappe boundaries on the presence of boundary springs (Schnabel,
10 1985) were given in the text.

11 **24. P1012 line 1: Why not used the generated lithological map to make this**
12 **portioning?? Why used a map that is not use the assessment?**

13 Unfortunately we have to state that we are not sure what our referee wanted to suggest in this
14 comment. We assume that the connection of the described lithological map to the
15 homogeneous modelling domains is not clear or misunderstood. In our model design we used
16 the lithological map, checked it for units which did not contain any landslides or which show
17 similarities regarding their geotechnical and topographical characteristics and merged the
18 respective units (for more details please refer to section 5.1). We did some changes in the text
19 of the revised manuscript.

20 Added to page 1012, line 1

21 The heterogeneity of geotechnical and topographical characteristics over a study area
22 should be considered when modelling landslide susceptibility (Blahut et al., 2010; Lee
23 et al., 2008). Modelling separately in lithology units is one approach to address this
24 heterogeneity (Petschko et al., 2012). This approach avoids the use of interaction
25 terms to represent lithology-dependent processes and preparatory factors, and thus
26 facilitates easier interpretation of the models. Fitting the model with individual
27 modelling domains based on the lithology units is expected to improve overall
28 predictive performance by accurately representing the diversity of geotechnical
29 conditions across the study area (Blahut et al., 2010; Petschko et al., 2012; Trigila et
30 al., 2013).

1 Accordingly, the study area was divided into 16 modelling domains based on a
2 simplified 1:200,000 lithological map (Fig.1; Schnabel, 2002; Bell et al., 2013). The
3 lithological map gives details on the parent material available for soil formation. This
4 determines the geotechnical characteristics on a scale of 1:200,000. Data on the parent
5 material was used as a proxy for these characteristics, as no appropriate geotechnical
6 data covering the entire study area was available. Lithology units with no observed
7 landslides were merged with geotechnically similar units to create homogenous
8 modelling domains (Tab. 1). The final susceptibility map of the province was obtained
9 by merging individual susceptibility maps.

10 **25. P1012 Modelling heterogeneous areas: If the area is so heterogeneous and the area**
11 **is already subdivided in homogenous areas, why not make the analysis in the single**
12 **homogenous divisions. This will make the assessment more accurate according to Blahut**
13 **2011, also the GAM model will fit better the data. Can the authors explain this?**

14 We agree on the possible source of misunderstandings found in this section. The lithological
15 units were used to represent the homogenous areas and therefore to split the study area in 16
16 modelling domains (please refer to line 21 on page 1012 in the original manuscript). These
17 were independently analysed regarding their landslide susceptibility, transferability,
18 consistency and spatially varying prediction uncertainties as presented in the original
19 manuscript. The results of the presented study show, that within these domains each domain
20 was fitted with a different set of variables. This strengthens the assumption that the division
21 into modelling domains is beneficial for the better characterisation of the susceptibility in the
22 study area. To clarify this section we changed the text and included the reference to Blahut
23 et al (2010) in the revised version.

24 For the changes please refer to our reply to comment 24 and the presented added text.

25 **26. P1013 Generalized additive model: I am not sure if I missed it inside the manuscript**
26 **but it is still not clear to me how was the overfitting of the model approached in this**
27 **analysis. Can the authors mention the model's functions on a table?**

28 As explained in section 5.2, overfitting is avoided or at least reduced through the selection of
29 nonlinear versus linear data transformations based on the AIC, which penalizes more complex
30 and flexible models. While other penalization or shrinkage procedures are available in the

1 statistical and machine-learning literature, the use of the AIC is well established in the context
2 of likelihood-based model fitting. References are included in the article, e.g. Hand (1997).

3 Section 5.2 also displays the general functional representation of the GAM. The possibly
4 nonlinear, spline-based transformation functions used in the 16 different GAM models are not
5 shown in the paper due to our focus on predictive performance and the limited space.

6 **27. P1016 line 6: What is the point of this? The results are already predisposed.**

7 This comment refers to criticism of Guzzetti et al. (2006) on the spatial partitioning of the
8 landslide data into training and test sample. Their discussion states “splitting the study area in
9 to two adjacent sub-areas can be problematic” as this approach assumes similar characteristics
10 of the independent variables (Guzzetti et al., 2006). However, the statement of Guzzetti et al.
11 (2006) is more understood as a word of caution, pointing out the possible pitfalls of spatial
12 partitioning of the study area. Therefore, this sentence was written, to explain that within the
13 domain similar variable characteristics are present. Concluding we find that our sentence is
14 not well understood without additional information on the statement of Guzzetti et al. (2006).
15 This sentence was moved into the discussion section on the spatial cross-validation.

16 **28. P1016 line 7: The authors should give relevant references in this part of the**
17 **manuscript.**

18 According to the referee’s comment relevant references were inserted in the text of the
19 revised manuscript:

20 Added to page 1016, line 7

21 We use non-spatial and spatial k-fold cross-validation to assess each model’s
22 predictive performance as a measure of the model’s non-spatial and spatial
23 transferability (Kohavi, 1995; Townsend Peterson et al., 2007).

24 **29. P1017 Section 5.4: The authors should describe the meaning of the transferability**
25 **and consistency indexes in a way that the reader is familiar with these terms.**

26 According to your suggestion more details on the meaning of the transferability and
27 consistency indexes were inserted into the revised manuscript.

28 Added to page 1017, line 2

1 The non-spatial and spatial transferability were expressed by the interpretation of the
2 estimated interquartile range (IQR) of the AUROC values resulting from the non-
3 spatial and spatial cross-validation of each modelling domain. The lower the estimated
4 IQR the better we considered the non-spatial and spatial transferability of the model
5 within the modelling domain. Sample size differences among modelling domains
6 result in differences in sampling variability of AUROC estimators, which then has an
7 influence on the IQR of AUROC among cross-validation repetitions. In order to
8 account for this contribution to sampling variability and be able to provide a
9 transferability measure that was comparable among modelling domains, the IQR has
10 to be adjusted according to the sample size.

11 Added to page 1017, line 17

12 Furthermore, the results of the non-spatial and spatial cross-validation provide an
13 estimate on the variable importance and the thematic consistency in each modelling
14 domain.

15 **30. P1019 line 13 to 18: I suggest including a figure regarding this.**

16 The quoted section describes the methodology of the lookup table of the standard errors. The
17 lookup procedure is only an auxiliary step or workaround to estimate prediction standard
18 errors. Given the limited space and the technical nature of this step, we feel that the inclusion
19 of an additional figure (e.g., scatterplot showing model fit) is not warranted. We added the
20 resulting R^2 achieved by using this method to transfer the standard error to the grid cells in
21 each modelling domain in Table 3. Accordingly, a short text describing the resulting R^2 values
22 was included in the revised version of manuscript.

23 Added to page 1024, line 19

24 The R^2 resulting from using the lookup table to transfer the standard errors to all grid
25 cells are ranging from 0.51 (in the Mélange Zone) to 0.9 (in Loess, Loam; Tab. 3). In
26 the Flysch Zone the computed R^2 was 0.82 which is only slightly better than in the
27 Bohemian Massif (0.79).

1 **31. P1022 line 10-14: Explain the reason why these reductions give better values but**
2 **decrease the transferability of the model. ...**

3 As described in section 5.4 the transferability of a model is better the smaller the interquartile
4 range (IQR) of the AUROC values estimated in the *k*-fold cross-validation is. Therefore, an
5 increasing IQR with decreasing sample size refers to a lower transferability. The
6 interpretation of the IQR and the transferability is explained in section 5.4. No changes made.

7 **32. ... P1022 Section 6.3: This is clear since most of the topographic influence of the**
8 **factors. How can this be overcome in this particular analysis?**

9 While we agree that the importance of topographic variable and in particular slope angle as
10 predictors is not a big surprise, we would like to keep this general statement unchanged before
11 entering into a more detailed review of variable importance in different geological units and
12 across different cross-validation repetitions. No changes made.

13 **33. P1024 line 1-5: I suggest including a table of errors.**

14 According to the suggestion a table of the logit-scale standard error (the minimum, maximum
15 and range) was included in Table 3.

16 **34. P1025 line 4-15 and P1026 line 5-10: The authors should clarify how this influences**
17 **the final susceptibility map and how to avoid this.**

18 The uncertainty assessment performed within this study assesses how the uncertainty may
19 affect the reliability of the map. The influences of the spatially varying prediction
20 uncertainties on the final susceptibility map were analysed in this study and have been shown
21 by an example in Fig. 6 and in the results section 6.4 in the original manuscript. Furthermore,
22 the influences of a smaller sample size on the AUROC value and the transferability of the
23 model were shown in section 6.2. The effect on the final susceptibility map was not analysed
24 directly. However, a lower AUROC value or a higher interquartile range of the AUROCs give
25 a comparably low model performance and transferability. Both analyses showed that larger
26 sample sizes are beneficiary to reduce the uncertainty related to sampling variability.
27 However, the avoidance of small sample sizes is a challenging task, as it could only be done
28 by increasing the landslide sample size (e.g. larger study area). This might not be possible in
29 some regions as no additional data on landslides (or data sources for mapping landslides) is

1 available. Another scenario might be that the region is just less susceptible so that only a few
2 landslides occurred. Instead we propose to add a clear analysis, presentation and discussion of
3 the uncertainties involved in the performed susceptibility modelling.

4 Added to page 1030, line 29

5 However, increasing the sample size can only be done by enlarging the landslide
6 inventory (e.g. by selecting a larger study area). This is challenging, as in some
7 regions no additional data on landslides (or resources for mapping landslides) might be
8 available.

9 **35. *P1026 Section Discussion: The discussion section should be more critical to the***
10 ***work and the difficulties found on it. So far it seems to replicate Section 2 with the***
11 ***assumptions made, the methodology used and some results. I suggest that this section be***
12 ***modified to include how the work can improve the quality of susceptibility maps and its***
13 ***transferability to other cases.***

14 The discussion was revised according to the referee's comment. For the changes on section
15 7.3 please see our reply to comment number 12. All other changes are presented here. In order
16 to provide a traceable text we decided to insert the entire sub-sections 7.1, 7.2 and the newly
17 introduced sub-section 7.4.

18 Added to line 1025, line 18

19 Practical challenges in this study arise from the size of the study area and the intended
20 output map scale of 1:25,000. The size of the study area brings along some limitations
21 regarding the availability of data sources that offer a full spatial coverage and a
22 reasonable map scale. This introduces a number of parametric uncertainties into the
23 modelling. Generally a complete, unbiased inventory would be desirable, as for
24 example a full inventory that was mapped directly in the aftermath of a landslide event
25 (single landslide or multiple landslides triggered at the same time) in the area of the
26 susceptibility map (Van Westen et al., 2008). This would allow for including land
27 cover or precipitation data in the modelling which might be helpful to learn even more
28 about the landslides in the area and to build scenarios on future landslide susceptibility
29 (or hazard / risk; Begueria, 2006b; Tarolli et al., 2011). However, a complete
30 inventory is rarely available. Particularly for historical inventories the level and type
31 of completeness is unknown while it is known that they are generally incomplete

1 (Malamud et al., 2004). Even a substantially complete inventory, which would be
2 useful in statistical modelling as it includes a substantial fraction (random sample) of
3 all landslides at all scales, land use types, lithological units or slope angles, cannot be
4 reached for historical inventories (Malamud et al., 2004). This originates from the
5 observation that landslides and their visibility on aerial photographs or other base
6 maps (e.g. hillshades derived from airborne laser scanning DTMs) are highly
7 influenced by new landslides, reactivation, erosion, land use type and anthropogenic
8 activities (Bell et al., 2012; Malamud et al., 2004; McCalpin, 1984; van Westen et al.,
9 2008). Furthermore the mapping and identification of landslides is highly dependent
10 on the experience and knowledge of the investigator (Van Westen et al., 1999;
11 Ardizzone et al., 2002; Harp et al., 2002). If these influences on the completeness are
12 not random they might introduce a bias in the inventory and furthermore in the
13 sampling which results in a model bias or systematic modelling error.

14 In our study area it is assumed that the inventory is not complete as it originates from
15 recent data sources (not multi-temporal) only and the visibility of landslides in the
16 ALS-DTM or orthophoto is influenced by human impact depending on the land use
17 type (Bell et al., 2012). Furthermore, a drawback is that no information on the time of
18 occurrence of the landslide is available. However, the type of incompleteness was not
19 analysed for the entire study area. Therefore, it is not clear if the missing landslides
20 are missing completely at random or are biased toward absence in certain land uses or
21 lithological units. The implications of an incomplete inventory on the model
22 performance (shown by the AUROC value) were estimated by performing the
23 repeated k-fold cross-validation using training and test sample. The results show rather
24 high AUROC values for most modelling domains, which indicates that even with an
25 incomplete inventory (training sample) the prediction of landslides of the test sample
26 was successful for most cases. However, sample size is of importance for the model
27 performance. For the discussion of this please see section 7.4.

28 **7.2 Quality of statistical model**

29 7.2.1 Study design to meet the heterogeneity of the study area

30 Observed variable-selection frequencies showed that different explanatory variables
31 were relevant in different domains, which provides additional justification to the
32 decision to model susceptibility in each modelling domain separately. Additionally,

1 not only the different choice of the variables is important but also the way the
2 variables are fitted or smoothed according to the sample in the respective domain.
3 Previous studies showed that within each lithological unit landslides occur at different
4 slope angles (Blahut et al., 2010; Muenchow et al., 2012; Petschko et al., 2012).
5 Similar differences within lithological units or terrain types might be present for other
6 explanatory variables as well, as the geomorphic and geologic characteristics change
7 (Lee et al., 2008). Facing this, our study design gives much more flexibility to
8 represent the characteristics of the study area. Furthermore, it incorporates information
9 on lithology by adjusting the odds of the prediction with the sampling rate of cells in
10 each lithological unit.

11 However, one may argue that with this approach problems occur at the boundaries of
12 the lithological units. Inaccuracies in the delineation of the lithological map of the area
13 have effects on the model results as the landslides might be assigned incorrect
14 lithological information. This may lead to an underestimation of effect sizes as data
15 from different (true) lithological units would be mixed. Similar mixing effects may
16 occur for quantitative predictor variables as well, for example as a function of
17 positional accuracy for scale and resolution. In regression this effect is known as
18 dilution, which may introduce a bias of estimated regression coefficients toward zero
19 (Frost and Thompson, 2000). As this would also occur using the lithological map as a
20 factor instead of as a mask for partitioning the study area, the boundary inaccuracies
21 are not only a problem in the applied study design.

22 7.2.2 Spatial and non-spatial cross-validation

23 We assessed the model form uncertainty by assessing a model performance estimate
24 by spatial and non-spatial cross-validation. Cross-validation estimation of a model's
25 predictive performance is a crucial step in predictive modelling because estimation on
26 the training set is always too optimistic (Hosmer and Lemeshow, 2000; Brenning,
27 2005). Cross-validation results in bias-reduced performance estimates as the test
28 partitions used in each repetition do not overlap with the training sample (Brenning,
29 2005). In particular spatial cross-validation is recommendable for spatial data, which
30 may be subject to spatial autocorrelation (Brenning, 2005; Brenning 2012a).

31 The median AUROC values estimated by spatial and non-spatial cross-validation were
32 generally similarly high in this study. However, the median AUROC values and the

1 transferability index clearly showed that non-spatial cross-validation provided a more
2 optimistic or even over-optimistic assessment of the model performance and
3 transferability in contrast to spatial cross-validation. Therefore, spatial and temporal
4 cross-validation should be preferred for performance estimation (Chung and Fabbri,
5 2008)(Chung and Fabbri, 2008). While spatial performance and transferability do not
6 necessarily reflect a model's predictive performance in the time domain, they provide
7 a more realistic assessment of its ability to generalize from the available data than
8 non-spatial approaches (Brenning, 2005).

9 The spatially and non-spatially least transferable models in this study were associated
10 with domains that had the smallest sample sizes. The relationship of sample size on
11 predictive abilities has also been shown in other spatial modelling studies (Stockwell
12 and Peterson, 2002; Hjort and Marmion, 2008). However, we believe that the cases of
13 high variation in AUROC values may be also related to the cross-validation sampling
14 variation as indicated by the difference between T_{sp} and lower T_{nsp} , and possibly the
15 proportion of stable and unstable terrain in a modelling domain.

16 Heterogeneity of landslide conditions (e.g. related to topography or land use) in the
17 cross-validation samples is more likely to occur if samples are partitioned spatially,
18 such as the case in spatial cross-validation. Here, similar characteristics of the
19 explanatory variables in both training and test sample are assumed and necessary
20 (Guzzetti et al., 2006). If this assumption is not met by the data (e.g. a rock type or
21 land use class is missing in the test sample) the transfer of the fitted model to the test
22 sample and the estimation of the model performance are difficult (or impossible)
23 (Guzzetti et al., 2006). In our study some model domains might have high contrast
24 between stable (e.g., large flat areas) and unstable (e.g., steep areas) terrain which
25 gives potential for greater variation of sampled terrain conditions; it may be possible
26 that in some samples one terrain condition is overrepresented relative to others. The
27 sampling strategy may be improved further by masking low-lying flat areas that are
28 not typically susceptible to landslides (Van Den Eeckhaut et al., 2009a; Goetz et al.,
29 2011). Consequently, the sample may have more potential to capture the
30 differentiating conditions of stable and unstable terrain in an area that is generally
31 susceptible to landslides (e.g., steep hillslopes). This might lead to a smaller variation
32 in the AUROC values.

1 The high importance of topographic variables in the susceptibility modelling goes
2 along with findings in other studies (Guzzetti et al., 2006; Begueria, 2006b; Van
3 Westen et al., 2008; Guns and Vanacker, 2012). However, it was rather surprising that
4 the soil data on permeability and void space was not selected more often during the
5 stepwise-variable selection. This might be related to the poor resolution of the soil
6 data (50 m x 50 m) and to the usage of topographic data as a proxy for hydrological
7 and soil characteristics (soil moisture and thickness). A strong correlation between the
8 topographic wetness index and soil characteristics was found amongst others by
9 Seibert et al. (2007). Furthermore, the higher resolution of the topographic variables
10 might be of advantage for better describing the local conditions of landslide
11 susceptibility.

12 Generally, the usage of rather static data in the modelling was a necessity resulting
13 from the available landslide inventory. However, this does not give the possibility to
14 include dynamic data on triggers into the modelling or to design scenarios of future
15 landslide susceptibility considering land cover or precipitation change. A clear source
16 of model form uncertainty is the concept of uniformitarianism in modelling. This
17 implies that the predisposing and triggering factors of landslides do not change in
18 future. However, natural variability of landslide triggering mechanisms and also of the
19 climate system might cause future changes. Currently, the influence of climate change
20 on current or future landslide activity is debated. However, no clear evidence on these
21 possible future changes was found in many regions (e.g. Crozier, 2010; Huggel et al.,
22 2012). Additionally, it might be possible that the most important data set explaining
23 the susceptibility might still be missing. This might happen although expert
24 knowledge on geomorphology was applied in selecting geomorphological relevant
25 data. Moreover, it has to be stated that this type of susceptibility map was designed for
26 main scarps of landslides. A classified map might cover the possible runout of
27 landslides but by definition does not show how the initiated landslides might move
28 downslope and endanger further areas (Demoulin & Chung, 2007).

29 Whereas a very strong thematic consistency was generally found for domains with a
30 large sample size and sampling rate, domains with small sample size and rate showed
31 a high variability in the variable-selection frequencies which gave a weak thematic
32 consistency. Therefore, the weak thematic consistency might also be associated with a

1 poor spatial and non-spatial transferability, both originating from a small sample size
2 and a small sampling rate. This relation was stronger for the spatial cross-validation,
3 while the thematic consistency from non-spatial cross-validation was unrelated.

4 Added to page 1030, line 29

5 **7.4 Considerations on sample size**

6 Summarizing the previously discussed findings some considerations on a minimum
7 sample size might be possible. While the transferability index is less strongly related
8 to sample size or sampling rate the thematic consistency index shows a stronger
9 relationship to them. Generally, larger sample sizes and sampling rates result in better
10 thematic consistency and transferability of the model. Furthermore, the minimum
11 standard error of the prediction was lower with larger sample size (Table 3).

12 The effect of a reduced sample size on the median and interquartile range AUROC
13 values was assessed in the Flysch domain. We found that the median AUROC
14 remained satisfactory high but decreased as sample size decreased, while the
15 interquartile range of the AUROC increased. Even with the smallest sample size the
16 model still achieved a good discrimination between landslide and non-landslide cells
17 according to the median AUROC value. Summarizing the results, a minimum sample
18 size with a sum of around 400 slide and non-slide cells might be recommended for the
19 methods applied in this study. This size leads to an acceptable transferability and
20 thematic consistency of the model in spatial cross-validation. However, examples
21 from successfully fitting a susceptibility model with smaller sample sizes (10
22 landslides with 15 cells each in an area of 177km²; Demoulin and Chung, 2007) give a
23 very contrasting result. Furthermore, the sample needs to be substantially complete
24 which might be difficult to estimate for small samples (Malamud, et al. 2004).
25 However, increasing the sample size can only be done by enlarging the landslide
26 inventory (e.g. by selecting a larger study area). This is challenging, as in some
27 regions no additional data on landslides (or resources for mapping landslides) might
28 be available on reasonable costs.

29 This study showed that the general trends found for sample size and sampling rate do
30 not apply for all modelling domains. Therefore, we highlight that the resulting quality
31 estimates (transferability index, consistency index and prediction uncertainty) might
32 additionally be dependent on a combination of the domain size and the landslide

1 density (landslides per km²). Also, dependencies on local terrain conditions and their
2 homogeneity in the modelling domain might exist.

3 Moreover, the geomorphic plausibility of the susceptibility map has to be analysed.
4 Previous studies found that high performance measures do not always guarantee high
5 geomorphic plausibility of the map (Bell, 2007; Trigila et al., 2013). It might be
6 possible that with a smaller sample size the geomorphic plausibility of the map is
7 lower. However, the influence of a small sample size on the geomorphic plausibility of
8 the susceptibility map is unclear. Nevertheless, analysing this was beyond the scope of
9 this study.

10 ***36. P1031 Section Conclusions: The conclusions are poor and do not reflect the results.***
11 ***This arises the question about the credibility of the created susceptibility map. Land use***
12 ***and the triggering effect are not considered in a correct manner....***

13 Regarding the comment on the incorrect dealing with land use or land cover and precipitation
14 data in our study, we have to disagree with the referee. We argue that given the available
15 landslide inventory we had no other choice than not including dynamic data in the
16 susceptibility assessment. This was pointed out in our previous replies to comments number
17 16 and 17. While this might be a clear limitation of the map, it has to be kept in mind that the
18 resulting landslide susceptibility map is still showing where landslides might occur in future
19 given the local terrain conditions. This might be assured considering the strong influence of
20 slope angle as a predisposing factor described in theory and the results of the variable
21 importance. Beside this the conclusion was completely rewritten and extended so that it now
22 also reflects the results.

23 Added to page 1031, line 1

24 High quality of landslide susceptibility maps is defined by the low aleatory and
25 epistemic uncertainties involved in the susceptibility modelling. This was analysed in
26 terms of landslide susceptibility model performance and spatially varying prediction
27 uncertainties of the final classified susceptibility map. The analysis gives an overview
28 and some estimates on the epistemic and aleatory uncertainties involved in statistical
29 susceptibility modelling. However, the effect of the propagation of all the single
30 uncertainties on the final map and subsequently to hazard and risk maps has to be
31 analysed further. Considering the present results in high model performance, analysis

1 and visualization of prediction uncertainties the applied model and resulting classified
2 landslide susceptibility map are regarded to be of high quality.

3 The applied study design with modelling in the different domains provides a high
4 flexibility for representing the characteristics of the heterogeneous study area.
5 Opposed to single hold-out validation the repeated k -fold cross-validation provides a
6 measure on the precision of the estimator and is independent of the one (random) test
7 sample. The spatial cross-validation gave a more realistic assessment of the model
8 performance and spatial transferability from the available data than non-spatial
9 approaches. This aids as an estimate on the model form uncertainty, which is
10 considered to be low.

11 A recommendation on an appropriate minimum sample size might be given
12 considering the presented analysis in different modelling domains and the tests on
13 reducing the sample size. According to the results the larger the sample size the better
14 is the transferability and thematic consistency. Therefore, also the quality of the
15 statistical model form increases with sample size. However, not all modelling domains
16 follow this trend. This might be related to a combined influence of the heterogeneity
17 or homogeneity of the local terrain conditions, the size of the domain and its landslide
18 density. A minimum sample size of around 400 slide and non-slide cells (200 each)
19 might be recommended for the methods applied in this study.

20 Only rather static data on local terrain conditions could reasonably be included in the
21 analysis given the landslide inventory, with no known landslide age. The stepwise
22 variable selection resulted in a satisfactory thematic consistency. Among the
23 geomorphologically relevant variables, topographic variables were selected with a
24 higher frequency than soil variables. This might be related to the spatial resolution of
25 the respective data. However, this result goes along with comparable studies having
26 topographic variables as the most frequently selected variables. The final landslide
27 susceptibility map gives a good representation of the landslide susceptibility based on
28 topography although the map does not include possible landslide triggers.

29 Regarding the susceptibility class uncertainties we conclude that the majority of the
30 study area is not affected by class uncertainties. Special attention has to be drawn to
31 possible overlaps of the low and medium susceptibility class in the predicted
32 probability map and the map of the upper confidence limit. A misclassification in the

1 low class might result in an underestimation of the susceptibility. This might have
2 adverse effects on the municipality or landowner if the recommendations for the
3 assignment of building areas might not be restrictive enough.

4 We discussed that there is a need of assessing, minimizing and communicating
5 uncertainties involved in susceptibility modelling. The analysis results need to be
6 communicated in an understandable manner to the stakeholder to allow for informed
7 decisions instead of giving an impression of certainty. A possible example was shown
8 by the visualization of the prediction uncertainty and its effects on the classified
9 landslide susceptibility map.

10 **37. ... Meanwhile, the other factors chosen are mainly dominated by the slope. Is it**
11 **surprising that the slope has the biggest influence on the results?...**

12 Van Westen et al. (2008) and surely also other authors stated that slope gradient (or here
13 called slope angle) is the most important factor in landslide susceptibility and hazard
14 assessment. In our analysis we had the opportunity to analyse if slope is still the most
15 important factor given all the other variables available in our study. We were not very
16 surprised that our results showed exactly that. However, it is also promising for a good model
17 and variable selection algorithm that the result could meet our presumptions. Much more
18 interesting for us was which other variables would show a high importance and if rather
19 newly used derivatives such as catchment height or the convergence index were worth being
20 introduced. This was assured considering the results on the variable importance gave a high
21 selection frequency of both variables. However, a detailed analysis of the benefit or drawback
22 of introducing or neglecting new variables in terms of its effect on the model performance
23 was not analysed as this was beyond the scope of our study. This was indirectly covered by
24 using a stepwise variable selection algorithm and the AIC criterion for identifying which
25 variables are contributing to a low AIC and low complexity of the model.

26 **38. ... How to include the propagation of uncertainties during the analysis? The papers**
27 **makes the susceptibility assessment feels like is not worth to use it for a decision making**
28 **process. ...**

29 This study was focussed on the analysis of the uncertainties resulting from the usage of the
30 statistical model and did not take into account any propagating error of epistemic or aleatory

1 uncertainties. This of course contributes to the overall uncertainties involved in the
2 susceptibility map and would be very interesting to analyse in a further study, but the focus of
3 this study was the analysis of the uncertainties resulting from the modelling with a statistical
4 model taking into account the standard error of the predicted probability of landslide
5 susceptibility. This will be pointed out more clearly in the revised manuscript.

6 Different methods for the propagation of uncertainties are reported in literature. However,
7 these mainly work with a probabilistic (Bayesian) approach (Hill et al., 2013). Therefore, it is
8 not straight forward how to include the standard errors of the prediction in analysing the
9 propagation of uncertainties. While there are many study designs available for the
10 probabilistic analysis of aleatory uncertainties, there is also still a need for further research on
11 the assessment of epistemic uncertainties and epistemic uncertainties with the presence of
12 aleatory uncertainties (Rougier and Beven, 2013). This analysis could be complementary to
13 the presented study. However, this was beyond the scope of this study.

14 **39. ... It arises the question: is it worth to make models more complicated or to simplify**
15 **them (since mostly the same results will be obtained) in order to make them understandable**
16 **and easier to communicate.**

17 As the development of new technology and computation resources are constantly available,
18 we state that it is always worth to consider new, maybe more complicated, methods or models
19 in order to be able to better represent the nature of the analysed process. As we did not
20 perform a comparison of the GAM with methods which might be considered as simpler we
21 cannot state if really the same results would be obtained. A study comparing the GAM to
22 generalized linear models (logistic regression) showed that the resulting AUROC and
23 sensitivity at 90% specificity values were significantly better using the GAM than using
24 logistic regression (Goetz et al., 2011).

25 However, we would like to point out that this study is not aiming to allow easier
26 communication of the models themselves but to enhance the communication on uncertainties.
27 This communication has to take place to allow for informed decisions of the decision makers.
28 It can be enhanced or aided e.g. by visualizing the prediction uncertainty in a map. Therefore,
29 these aspects of uncertainty need to be analysed first, so that they can be communicated later.

30

31 **Figures and table comments**

1 **40. Table 1: What is the point of adding a median slope angle? Is this relevant to the**
2 **final assessment? ...**

3 Please refer to our reply to comment 15. The median slope angle is not directly relevant to the
4 final assessment. It was only used as a simple measure to describe the topographic
5 heterogeneity of the study area.

6 **41. ... As mentioned in the paper, these are geotechnical parameters but I can not see**
7 **any type of geotechnical parameters (i.e. strength parameters) but just a lithological**
8 **description. ...**

9 Unfortunately no detailed data set on geotechnical properties (e.g. friction angle, cohesion or
10 specific weight) covering the entire area is available. This data is only available very locally
11 where detailed soil analysis was performed in the context of a slope stability survey.
12 However, it can be stated, that the geotechnical parameters are determined by the parent
13 material available for the soil formation. Therefore, we took the material of the lithological
14 unit as a proxy for the geotechnical characteristics predominant in this unit.

15 We added some more details in the revised manuscript to clarify this.

16 Added to page 1012, line 22

17 The lithological map gives details on the parent material available for soil formation.
18 This determines the geotechnical characteristics on a scale of 1:200,000. Data on the
19 parent material was used as a proxy for these characteristics, as no appropriate
20 geotechnical data covering the entire study area was available.

21 **42. ... Besides this the table is confusing and not easy to grasp. For example, there are**
22 **more landslides in a 12.6 degree median slope than a 20.2 degree median slope and the one**
23 **with 16.6 degrees has very few. Problem arises when looking at the density, there are 4.27**
24 **(density) slides in a slope of 4.8 degrees which is a fine sand silty marl but there are 2.08**
25 **(density) in 20.2 degree limestone, marl and sandstone. I suggest adding more relevant**
26 **information to the table.**

27 This table was included in the manuscript to show the heterogeneity of the study area and of
28 some predisposing conditions of landslides in the area. Landslides were mapped in the entire
29 area and therefore we are confident that this table is representative for the actual distribution

1 of landslides in the study area. As stated by the referee a high landslide density is found in
2 areas with a median slope angle of 4.8 degree while areas with a much higher median slope
3 angle (20.2 degree) show a much lower landslide density. This can mainly be traced back to
4 the different predominant material and its weathering products in the different lithological
5 units. These details emphasize the need for fitting the model in the different modelling
6 domains. Therewith, it is much easier and straight forward to consider the different
7 predisposing conditions in the lithological units. No changes made.

8 ***43. Table 2: Once again, this seems to be a topographic susceptibility map only***
9 ***influences by the topography (according to the table values). Hydrological factors can be***
10 ***almost discriminated while in reality this is a very important factor in terms of triggering***
11 ***and soil conditions. I suggest revising this carefully.***

12 Due to the available landslide inventory we decided to not include any dynamic data (land
13 cover or precipitation) in the modelling of the landslide susceptibility. This was addressed
14 more thoroughly in our reply to comment 16 and 17.

15 This table shows the results of the stepwise variable selection applied in our study. Therefore,
16 the variable selection can be considered as rather objective and not influenced by any
17 subjective expert knowledge. The case that the soil data was not selected as often as it would
18 be expected from the expert point of view might be related to the poor resolution of the soil
19 data. Furthermore, we argue that the topographic data (slope, topographic wetness index,
20 catchment height and convergence index) might be a very good proxy for hydrological and
21 soil conditions in the field (as shown by Seibert et al., 2007). This and the better resolution of
22 the derivatives from the LiDAR DTM might explain the preference of the model to select
23 topographic data for modelling the landslide susceptibility. Additionally it is not a
24 topographic susceptibility map only as the differences in the lithology are taken into account
25 by including the sampling rate in the susceptibility map.

26 No changes were made as we consider our results as trustworthy. Some of the considerations
27 were included in the discussion of the manuscript.

28 Added to page 1029, line 3

29 The high importance of topographic variables in the susceptibility modelling goes
30 along with findings in other studies (Guzzetti et al., 2006; Begueria, 2006b; Van
31 Westen et al., 2008; Guns and Vanacker, 2012). However, it was rather surprising that

1 the soil data on permeability and void space was not selected more often during the
2 stepwise-variable selection. This might be related to the poor resolution of the soil data
3 (50 m x 50 m) and to the usage of topographic data as a proxy for hydrological and
4 soil characteristics (soil moisture and thickness). A strong correlation between the
5 topographic wetness index and soil characteristics was found amongst others by
6 Seibert et al. (2007). Furthermore, the higher resolution of the topographic variables
7 might be of advantage for better describing the local conditions of landslide
8 susceptibility.

9 **44. Table 3: It is a nice table but can be linked to table 1 in order to give space to other**
10 **figures. This can be the authors decision of they think the table is relevant enough.**

11 Regarding the suggestion of integrating table 3 into table 1 we would like to refer to comment
12 33 where it says that table 3 was expanded with columns on the standard error occurring in
13 each domain. No further changes made.

14 **45. Figure 7: Nice figure but it would be good to see it displayed on a map to have a**
15 **better grasp of the concept.**

16 We agree with the suggestion of the referee. However, due to the already reached length of
17 the paper and large amount of figures we will not provide an additional figure showing this.
18 Figure 7 was adapted to better show the connection to Figure 6 in the original manuscript.

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