Response to reviewer comments on hess-2019-602

June 20, 2020

Dear Dr. Nunzio Romano,

herewith we submit the revised version of the manuscript hess-2019-602 “A systematic assessment of uncertainties in large scale soil loss estimation from different representations of USLE input factors – A case study for Kenya and Uganda”. We would like to thank you for handling the manuscript and would also like to thank the three anonymous reviewers for their constructive reviews. We have considered and responded to all comments in the revised version of the manuscript to the best of our knowledge. Below we added all reviewer comments, our initial suggestions to revise the manuscript, a detailed documentation of the decision and changes we made for the manuscript revision, as well as a document indicating the differences between the revised and the original version of the manuscript.

We hope the revision of the manuscript satisfactorily replies to all of the comments made by the reviewers accordingly. If there are any further questions or any further issues from our side to handle, please contact me and we will try to clarify them as soon as possible.

Sincerely,
Christoph Schürz

Reply to the reviewer comments RC1: 'Hess – USLE model Uganda' by Anonymous

Referee #1

We would like to thank the Anonymous Referee #1 for the very constructive review and the valuable comments to improve the quality of the manuscript. We appreciate the positive feedback on the manuscript. In the following, we addressed each comment individually. The reviewer comments are printed in *serif, italic font*. Our replies to the individual comments are written below each comment in black non serif font. The actual changes in the revised version of the manuscript are outlined in blue non serif font. The literature that was cited in the reply is added at the end of the document.

An interesting article proposing interesting aspects in USLE modelling: a) uncertainties b) comparison of factors c) validation. However, there are issues that authors should face in order to improve the quality and proposing it for publication.

An important issue is that authors did not propose 'solutions'. They did the 756 USLE simulations but they should also propose which is the most representative one per factor. For example , which is the best method for the R-factor?

All realizations that were developed for each USLE input are based on methodologies that were proposed and implemented in peer reviewed studies. In the summary of methods for the calculation of (R)USLE inputs that was compiled by Benavidez et al. (2018) most of the methods that were implemented in the present manuscript were listed as 'valid' methods to compute the respective USLE input. The basic rule for the input generation in this manuscript, was that if a method was implemented in a peer reviewed study in Eastern Africa (or regions with comparable climatic/topographic/vegetation conditions) before, it is considered as a plausible method for the generation of that input. From this perspective , all input realizations must be treated as equally adequate representations of that input.

The aim of this study was to assess the uncertainties which are inherent in the calculation of the long-term mean annual soil loss simply due to the choice of the methods for the calculation of the USLE inputs. It has never been the intention of this study to identify a 'best' realization for a USLE input. Any attempt to identify plausible or implausible USLE model combinations would have failed, as no measured (or other) data was available that could support a decision to verify or falsify a model combination. This was addressed in detail in the Sections 4.4 and 5.2 that highlighted the limitations of a comparison to the limited observation data that is available for the investigated study region. We suggest to revise these sections and try to strengthen the stated arguments to clarify the present limitations of model falsification.

In the revised version of the manuscript we added the section 5.2 "USLE input realizations - Ranges, plausibility, and their comparison to other studies" in the discussion. The section puts the input realizations into a reference with other large scale studies and contains some thoughts on the plausibility of some of the calculated input factors.

Authors propose new approaches to check the plausibility of large scale assessments based on Bosco et al., 2014. This study has neither been peer reviewed nor published. So, I would suggest using published literature studies for such statements.

Bosco et al. (2015) briefly outline the methodology that is explained in much greater detail in Bosco et al. (2014). While Bosco et al. (2015) is a peer reviewed article, we agree that Bosco et al. (2014) is published as a pre-print version that was not peer-reviewed. In the present manuscript we always refer to both articles when we mention the applicability of remote sensing data for a plausibility check of the USLE simulations. Although Bosco et al. (2014) is not peer reviewed it provides valuable information that can be accessed via a DOI and therefore the same document is available to the reader of this study to which we referred to when compiling this work.

Based on our argument we kept the reference Bosco et al. (2014) in the revised version of the manuscript. Yet, we specified sections where we refer to the methods proposed by Bosco et al. (2014) (e.g. P27 L26-28 of the previous version of the manuscript).

In a similar study, Estrada-Carmona et al (2017) made a global sensitivity analysis of USLE input factors. Please compare the results of your study with the ones of this study.

Thank you for drawing our attention to this study. Although the approach presented in Estrada-Carmona et al (2017) differs from the approach that was presented in the present manuscript we should and will refer to this study.

In the revised version of the manuscript we added a brief literature review on the implementation of uncertainty and sensitivity analysis to evaluate the soil loss estimates and the impact of the USLE inputs on the soil loss estimates on P4 L2ff

Further, results of the reviewed studies that were summarized in the introduction were included in the discussion section 5.3.

The most recent study that I found in East Africa is the one of Fenta et al., 2019 Science of the Total Env. How your results compare with their results?

The study of Fenta et al. (2020) was not published by the time this manuscript was compiled. The workflow that is presented in Fenta et al. (2020) was adopted from Borrelli et al. (2017), Panagos et al. (2015), and Panagos et al. (2014) for the computation of the USLE K and C factors. To calculate the LS factor the method of Desmet and Govers (1996) was implemented. These three realizations for the inputs K, LS, and C are also members of the input sets in this study and should therefore result in comparable ranges. Interesting aspects in Fenta et al. (2020) are the computation of R and more importantly the consideration of soil protection measures represented by the P factor. Thus, a comparison of the calculations presented in Fenta et al. (2020) with the calculated ranges of soil loss in this study is valuable. We suggest to refer to Fenta et al. (2020) in the revised version of the manuscript.

We set the USLE ensemble soil loss estimates into reference with the findings reported in Fenta et al. (2020). Fenta et al. (2020) provided country wide mean soil losses, these were compared to the ensemble median, minimum and maximum soil loss estimates calculated with the USLE model ensemble and averaged for both countries. The comparison was added in section 4.1. Fenta et al. (2020) also report on area proportions for soil loss levels in the countries of East Africa. We compared their findings with the results of the USLE model ensemble and added the following figure to the revised version of the manuscript:

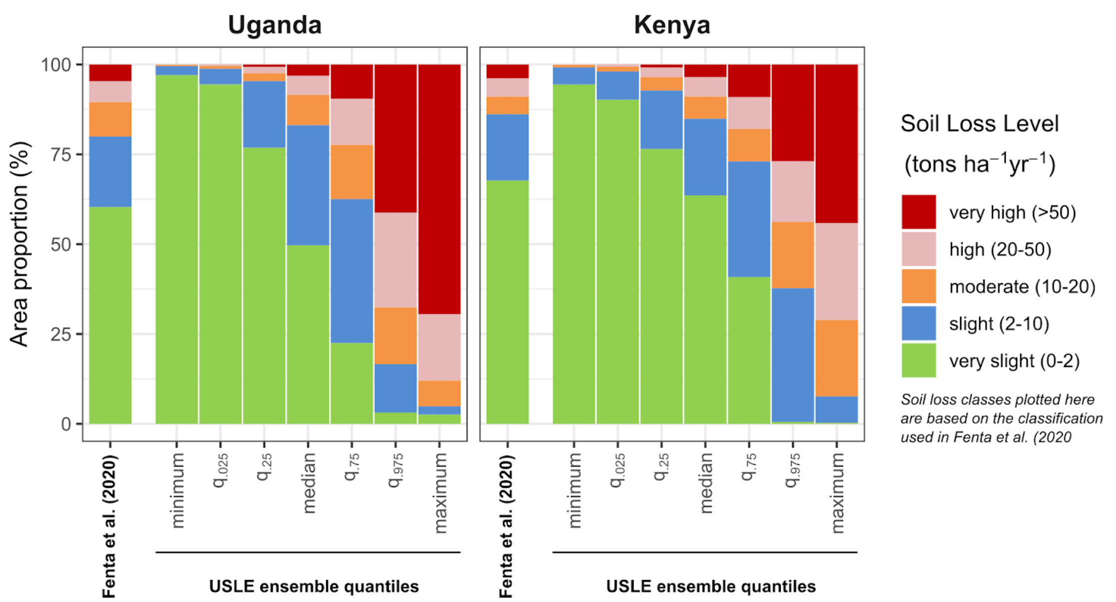

Figure 4. *Comparison of the proportions of the areas in Kenya and Uganda that are summarized with different soil loss levels. The comparison shows the results reported in Fenta et al. (2020) to the results of the 972 USLE model realizations. The analyzed quantiles represent the soil loss quantiles in each grid cell that result from the USLE model ensemble. For the comparison the soil loss levels applied in Fenta et al.(2020) were used.*

Soil losses estimates with USLE are long-term averages. You cannot compare the long-term findings against short-term findings in plot experiments.

We agree that a comparison of long-term soil loss to short term measurements of e.g. sediment yields is improper. In the manuscript we specifically indicate the limitations of the comparability of USLE simulations to an instream monitoring of sediment yield. Yet, it is a common practice to employ short term records of observed soil loss (or sediment yield) to validate the results of a USLE model. See e.g. Fenta et al. (2020) where a comparison of USLE results to 'measured' short term sediment yields was performed.

Thus, we see a relevance to critically address the issue of a USLE model comparison to observation data. Eventually, the analysis of the USLE model ensemble and its comparison to the soil loss data collected by García-Ruiz et al. (2015) clearly supports a critical view on such model validation and is therefore in our opinion a relevant contribution to the soil erosion literature.

Based on our arguments stated above we think it is relevant to keep the sections on model validation. Thus, the sections 3.7, 4.4, and 5.2 are still present in the revised version of the manuscript.

Authors made a classification of soil erosion rates. The tolerable soil erosion rate cannot be justified according to literature findings as the soil formation rates are low. This means that sustainable soil erosion rates are lower than 1-2 t per ha per year. In addition to this, authors present some really extreme mean annual soil loss rates >200 -1,500 t ha-1 yr-1. This means that at least 2 cm of soil is lost every year. This may be the case for very limited areas; otherwise we risk to lose completely our soils in50 years. This means that some of the estimated combinations are not realistic. You should not be driven by the modelling outputs but somehow use also the common logic(you cannot lose 1m of soil in 50 years).

We have refrained from making judgments about tolerable soil erosion rates, but we do point out that such values exist in the literature. The concept of this manuscript was to employ the information that we acquired from the peer reviewed literature to represent the current status of knowledge on the topic of "soil erosion by water" and the assessment of water erosion with USLE type models. This idea also is applied to the selection of soil loss classes that employ what is common practice in the literature. At no point in the manuscript do we imply that a soil loss of 10 t ha^{-1} yr^{-1} is indeed the value where the soil loss is compensated by the soil formation. We stated that suggested literature values range from 5 to 12 t ha^{-1} yr^{-1} and that several studies in Eastern Africa used 10 t ha^{-1} yr^{-1} as a threshold value. Due to the absence of more reliable values, we based the classification on literature values that included threshold values of 10 t ha^{-1} yr^{-1}. Yet, we agree that threshold values of 1 or 2 t ha^{-1} yr^{-1} would be valid assumptions as well. Fenta et al. (2020), for example, classify soil loss by water as 'very slight' soil loss when the soil loss is in a range between 0-2 t ha^{-1} yr^{-1} and as 'slight' when the soil loss is in a range between 2-10 t ha^{-1} yr^{-1}. Yet, Fenta at al. (2020) do not provide any reference on which their classification is based. In conclusion the classification of soil loss always involves a highly subjective view on the calculated soil losses. A classification should primarily reduce information and support the reader in the interpretation of data and we are aware that poorly chosen class names can mislead the reader. Nevertheless, we decided to use a classification that was implemented in the literature before and should be considered to be as valid as any other classification.

We agree with the reviewer that calculated soil losses of over 200 t ha^{-1} $yr^{-1}$are extreme. Nevertheless, for the informative value of this manuscript it is relevant to keep these model combinations as potential USLE realizations. Two arguments for the value of these model members are as follows:

Indeed such high values were calculated only locally and only by a few model combinations. This is exactly what this manuscript tries to address. Models can be wrong. Thus, if other representations of the USLE estimate soil losses that are substantially lower then the modeler has a chance to evaluate such large soil loss estimates based on other estimates. Yet, with a single model approach (that is common practice in the literature) it is simply infeasible to evaluate large calculated soil losses if no reference by observation data or a model ensemble is given. Thus, if a model setup calculated excessive soil losses locally, what does this mean for the evaluation of the remaining areas in a study region?

USLE type models do not account for soil deposition and therefore do not reflect the sediment balance. Thus, the soil that is strongly eroded locally is also deposited and not completely lost but displaced.

We think that we substantially commented on the issue raised by the anonymous referee #1 above. Thus, we prefer to keep the class boundaries that we used in the classification in the previous version of the manuscript. We changed however the term ‘tolerable’ to ‘slight’ and added a sentence to explain why we avoid using the term ‘tolerable’.

To allow a better comparison of the model ensemble simulations (and particularly the average and extreme ranges of the estimated soil losses) we referred to the findings of Fenta et al. (2020) (see comment above)

Title: I would replace the word ‘representations’ with ‘applications’

We think that ‘applications’ is not the appropriate term for the entities that we analyzed in this work. ‘Applications’ could also imply an application of USLE inputs in for instance different independent studies, or locations and would thus be misleading. In this manuscript we represented the USLE input factors R, K, LS, and C for the same study by employing different methods to compute them and would therefore prefer to use the term ‘representation’ or ‘realization’ when we refer to one member in the set of realizations for a USLE input.

We kept the terms ‘representation’ and ‘realization’ to define a layer that was calculated for one of the USLE inputs employing a specific method from the literature in the revised version of the manuscript.

P4 L15-24: This paragraph is not needed.

We agree that this paragraph does not provide any new information, but outlines the structure of the manuscript. We think that this is a subjective question of style and preference and believe that it helps the reader to get an overview of the content of the paper at hand.

Based on our arguments we preferred to keep the paragraph in the revised version of the manuscript.

Fig. 3: attention in the measurement unit of soil erosion. It is better to use t ha-1 a-1. If you want to keep your proposed unit , then please put in parenthesis (ha a)

Thank you for pointing this out! We will revise the units in all figures to be consistent with the units in the text and tables.

All figures in the manuscript were revised. The units in all figures and maps are now written in round brackets. The unit style now agrees with the style that was used in the text of the manuscript.

Fig 7. It should be applications and not realizations.

See the response above. The same argument applies as above for the title of the manuscript.

See the comment above.

P23 end of the page and P24 beginning of the page: I would propose that some applications of the factors can be excluded. For example, the NDVI application is known to have very low C-factor results and it is known to have incorporated some problems. The same applies for R-factor. For example the methods of Lo and Fournier are based on rainfall amount and do not incorporate the rainfall intensity.

As responded previously, the goal of this work was to provide a comprehensive assessment of frequently implemented methods to calculate the USLE input factors and to evaluate the uncertainties in the soil loss estimates that arise from the input uncertainties due to the impact of different methods, published in peer-reviewed journals, to calculate the model inputs. Thus, it was not our intention to judge the implemented methods, but to consider them as potential methods if they have been implemented in similar study settings. This also applies to the methods used to calculate the R factor and the C factor.

Both methods addressed by the Anonymous referee #1 (the implementation of the NDVI and the method of Lo et al. (1985)) were recently implemented in a large scale soil loss assessment by Karamage et al. (2017). In general, the implementation of methods that use long-term precipitation instead of rainfall intensity is common due to the absence of rainfall intensity records. Thus, in terms of a comprehensive uncertainty assessment we must consider these types of methods for the calculation of C and R as well.

Concerning the limitations of any implementation of the NDVI to calculate C, we were not able to find information in the literature that NDVI is known for a calculation of low C-factor values. Yet, the analysis that we illustrated in Fig. 7 of the manuscript would support that statement for the selected region in Uganda. Also, any well documented issues with the application of the NDVI to calculate the C-factor is not known to us (or is at least not reported in the literature at hand). However, we specifically address in the manuscript that the method of Van der Knijff et al. (2000) was never validated against ground truth data.

Concerning the C-factor value ranges calculated with the method of Van der Knijff (2000) we want to take the analysis in Fig.7 of the manuscript as an example. Although the mean values and the quantile values for the C-factor with the NDVI are significantly lower to the other methods, the absolute ranges of C-factor values when employing the NDVI are in a plausible range. For Europe Panagos et al. (2015) calculated C-factor values as low as 0.00116 for forests and C-factor values of up to 0.2651 for sparse vegetation. The ranges presented in this manuscript are in line with the range presented in Panagos et al. (2015).

We see however that a comparison to other large scale studies would provide valuable information and will consider that in the revised version of the manuscript.

In the revised version of the manuscript we added a section in the discussion (section 5.2) to compare the values of the calculated USLE input factor realizations to the ranges in other large scale studies.

P19 the same as above. Are values of K-factor 0.088 acceptable? Can be compared to other findings in the literature?

Panagos et al. (2014) for instance calculated a range for the K-factor of 0.004 – 0.076 t h MJ^{-1} mm^{-1}. Naipal et al. (2015) implemented the method of Torri et al. (1997) that resulted in such large K-factor values in this manuscript. Naipal et al. (2015) also applied a K-factor value of 0.08 to volcanic soils as these are particularly erodible. Although single grid cells in the analysis in this manuscript exceed the mentioned literature values, the calculated values are not completely out of range.
Yet, we fully agree that it is relevant to set the calculated values into a reference with other literature. We suggest to add a comparison to the above mentioned literature values and additional literature in the revised version of the manuscript.

See the comment above

P20 L1-10: The same as above. Can you prove that values of C-factor 0.03 are acceptable in agricultural areas?

Thank you for raising this point. The same arguments as in our replies to the previous two points apply here.

See the comment above.

5.2 section. It is not proper to have a section with question.

We cannot verify this point, as the manuscript guidelines do not disallow questions as section headers. This should be, in essence, the freedom of the authors. See Blöschl and Montanari (2010), Savenije (2009), or Schürz et al. (2019) as examples with questions as section headers.

The discussion section was completely restructured. Thus the section headers also changed.

P25 L30-34: Is It possible to validate large scale models with Google Earth? GoogleEarth can potentially verify permanent erosion characteristics (e.g. gully erosion) and not rill and sheet erosion. The plausibility of large scale studies can be verified with model applications at regional or local

We cannot confirm the feasibility of the implementation of satellite imagery for the validation of soil loss assessments. It was not our intention to illustrate such an approach as a verified method for the validation of large scale soil loss assessments. From a technical perspective it should however be possible to employ multi-angle high resolution imagery for different time steps to apply any stereographic analysis. Furthermore, intense soil erosion might be visible in satellite imagery and can be related to an erosion class, which would allow a use as 'soft' information for model validation. Regardless of the exact approach to employ satellite imagery, the conclusion in the presented manuscript was that our traditional approaches of model validation failed in this large scale study (and would likely fail in others) and new concepts for model validation would be valuable to be implemented in large scale assessments. The validation of a large scale model application with a model application at a smaller scale does not sound plausible unless the small scale model is validated, as any soil erosion model involves uncertainties.

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Reply to the reviewer comments RC2: 'Referee comments and suggestions' by Anonymous Referee #2

General comments

The paper presents a large scale assessment of the uncertainties in USLE soil loss estimation as a consequence of different realizations and combinations of the corresponding input factors. A total of 756 USLE model setups were examined with a spatial detail of 90 meters (cell size). Moreover, the case study (Kenya and Uganda) is vast enough to include a great variability of topographical, climatic and land use conditions. For these reasons, the ranges of both input factors and soil loss are very wide, contributing to improve the scientific reliability and interest of the work. The spatial variability of the model sensitivity to the different factors was examined and discussed. An attempt to compare/validate the simulated soil loss with field soil loss data was also made. All the sections of the paper are very clear and the scientific background is well detailed and discussed. The degree of agreement between the estimates obtained by the different input ensembles was evaluated not only on the basis of the quantitative values, but also and above all on the basis of the soil loss category (tolerable,moderate, high and severe). This is in fact the most rational approach for a model characterized by high uncertainty.

We would like to thank the Anonymous Referee #2 for their positive and supportive feedback on this manuscript, the very constructive review and the valuable comments to improve the quality of the manuscript. In the following, we addressed all the comments made by the Anonymous Referee #2. The reviewer comments are printed in *serif, italic font*. Our replies to the individual comments are written below each comment in black non serif font. The actual changes in the revised version of the manuscript are outlined in blue non serif font. The literature that was cited in the reply is added at the end of the document.

Specific comments

Lines 3-6 pag. 3. I suggest to mention other recent promising modifications of the USLE, such as those proposed and tested by Bagarello et al. (2010) and Di Stefano et al. (2019): - Bagarello, V., Ferro, V., Giordano, G. 2010. Testing alternative erosivity indices to predict event soil loss from bare plots in Southern Italy, Hydrological Processes 24(6) , 789-797. - Di Stefano, C., Pampalone, V., Todisco, F., Vergni, L., Ferro,V. 2019. Testing the Universal Soil Loss Equation-MB equation in plots in Central and South Italy, Hydrological Processes 33(18), 2422-2433

Both suggested references describe the modification and improvement of the event based USLE-M model (Kinnell, 2010). In the manuscript the topic of event based soil loss assessment with USLE type models was not addressed, but we focused on long-term annual soil loss assessment to limit the breadth of the manuscript content. To write an additional paragraph and acknowledge all (or many) USLE derivatives would be out of the scope of this study.

Based on our arguments, we preferred to keep a focus on the “traditional” form of the (R)USLE and analyze it with respect to uncertainties that result from different realizations of the USLE inputs. Thus, we refrained to additionally discuss further USLE derivatives. Yet, as the focus should be uncertainty and sensitivity analysis, we added a section on uncertainty and sensitivity analysis with USLE type models in the revised version of the manuscript on P4 L2ff and in the discussion section 5.3 to provide a better foundation for our work.

Figure 1. I suggest to check the legend of the figure 1a, in which the erosion risk is represented according to a discrete classification based on only three colours (white,yellow and pink). However, from the figure, the colour grey is also widely present and gradients for both yellow and pink are evident. I think that a discrete classification/legend is not correct.

We understand that the maps together with the provided legends can be confusing to the reader. Therefore, we suggest to revise the legends and the figure caption of Fig.1 the following:

- The legend symbol for ‘Very gentle inclinations…’ will be changed to add a slash in the box, thus indicating that no color was applied for that class.
- Will will add the information that the hillshade is plotted in grey as a background layer.

The discrete erosion risk classes were taken from Ebisemiju (1988) and provide a reasonable first differentiation of erosion risk in the study area. We tested a continuous color ramp to visualize the soil risk while compiling the manuscript. The information was however not presented well in such a visualization. Therefore, we would prefer to remain with only three soil risk classes.

Fig. 1 was strongly updated in the revised version of the manuscript. We tried to improve Fig. 1 as follows:

- The legend symbol for ‘Very gentle inclinations…’ was changed and a slash was added in the box to indicate that no color was applied for that class.
- The information that the grey background shows the hillshade was added in the figure caption.
- The unit style was changed to match the units in the text.
- A panel showing the Seasonality Index (SI; Walsh and Lawler, 1981) was added to provide information on the spatial distribution of the rainfall seasonality (see also comment below)

The updated figure is illustrated below:

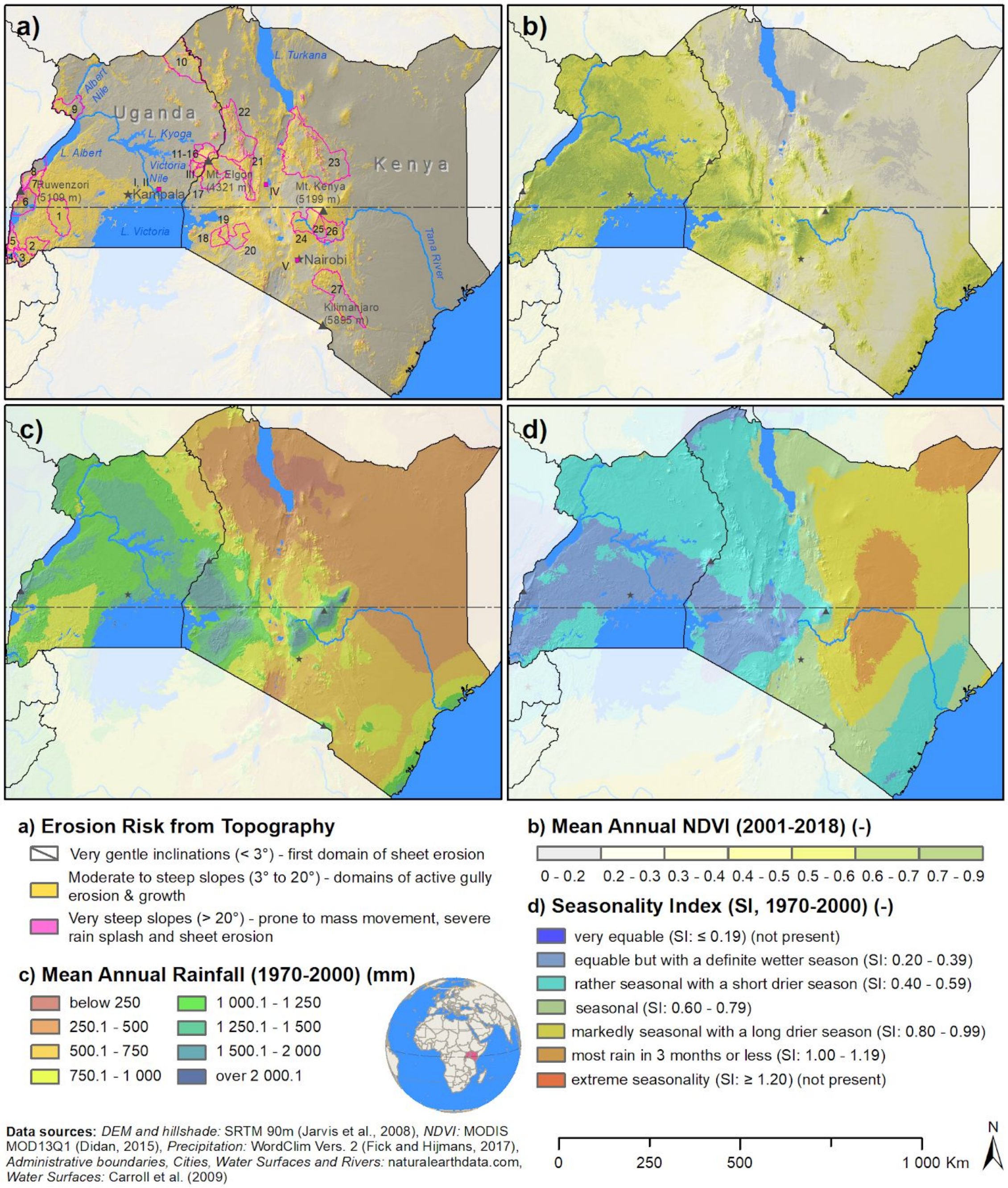

Figure 1. I understand that the purpose of Figure 1 is just to provide a rough description of the erosion-prone areas according to topography, vegetation cover and rainfall amounts. In relation to this last aspect, however, the authors could have chosen a proxy more appropriate than the annual precipitation: in fact it is well known that the distribution of rains has a determining role in soil loss. In particular, several studies in the literature have shown that in some areas, the annual soil loss is highly correlated with the erosivity of a few erosive events. Therefore, other synthetic indices (e.g. the Modified Fournier Index (Arnoldus, 1980) could be proxy more reliable than annual precipitation in the description of the susceptibility to erosion due to rainfall characteristics).

We think that the Modified Fournier Index (MFI, Arnoldus, 1980) can be an interesting index to characterize the erosion risk in the study region. Therefore, we suggest to calculate the MFI for the study region and analyze the spatial pattern. If the shown patterns strongly differ from the patterns of the shown long-term annual precipitation we suggest to add a panel to additionally show the MFI in Fig.1.

Please see the comment and the Figure above to also see the changes that were made based on this comment.

Lines 5-13 pag. 8. As stated by the authors themselves (section 5.3), it is not possible to consider all the available methods for the calculation of USLE input factors and the authors made plausible choices in their selections. However, the authors started their analysis of the R factor by aggregating the long-term monthly amounts to the annual scale, thus losing the possibility of applying the methods that derive the R factor from both annual and monthly precipitations. The reasons for this choice should be provided.

We agree that the aggregation of long-monthly precipitation to long-term annual precipitation reduces the information that is provided by the data. The simple reason why primarily long-term annual precipitation was implemented to calculate the rainfall erosivity factor, was that the literature on large scale soil loss assessments as well implemented primarily long-term annual precipitation products to calculate the rainfall erosivity.
We agree with this comment that this decision in the analysis must be discussed. We suggest to perform a comparison of the application of the MFI (Arnoldus, 1980) with the methods that were implemented in the manuscript. We suggest, however, to add any analysis in the supplementary materials and add a section on monthly rainfall erosivity in the discussion.

To account for the seasonality of the rainfall we additionally added one realization to the set of R factor realizations that employs the MFI to calculate R factor values. The set of realizations for the rainfall erosivity R now includes two additional realizations that were presented in Fenta et al. (2017), where one method employs long-term mean annual precipitation to calculate R and the second method uses the MFI to account for the seasonality of the rainfall. Fenta et al. (2017) applied both methods in a large scale study in Eastern Africa. As a result 972 realizations of the USLE model are analyzed in the revised version of the manuscript, compared to the 756 realizations that were presented in the previous version of the manuscript.

Section 5.2. the discussion presented in this section was expected since the authors described in section 3.7 their intent to compare simulated yields with those collected from field observations. I agree that there are several limitations and difficulties, but the attempt is appreciable. I wonder if another possible reason for the lack of agreement could be represented by the differences between the land use at the time of field experiments and the average one considered in the simulations, (e.g. Sutherland and Bryan (1990) refers to experiments carried out before 1990, whilst the MODIS NDVI data are from 2000 to 2012).

We think that the Anonymous Referee #2 raises a very relevant point here. In the manuscript we addressed a few selected, but certainly dominant limitations for the comparison of in-field data with the calculated soil losses. Yet, other possible sources that can potentially limit a comparison were not mentioned (such as the addressed impact of land use change, particularly as deforestation in the previous century is a frequently mentioned issue for soil loss in Eastern Africa). We suggest to add other potential limitations for the comparability of in-field data to the calculated soil losses in the discussion section 5.2.

We added the following paragraph in the discussion in section 5.2:

Apart from the short monitoring periods that are often available from reference studies it is likely that the (remote sensing) data that was employed to calculate the USLE input factors and to assess the soil loss do not reflect the conditions that were present during the monitoring period in a study region, simply because the monitoring period and the period for which input data are available do not overlap. Soil cover by vegetation perfectly illustrates the issue. Monitoring data can date back several decades (e.g. Sutherland and Bryan (1990) in our case). On large scales the vegetation cover is often estimated by employing remote sensing satellite data that can be more recent than monitoring data. Particularly, in East Africa deforestation affected the land cover over the past decades with reported decreases in the forest biomass of up to 26 % in Uganda (Jagger and Kittner, 2017), or forest clearances in protected forests in the Mt. Elgon region of 33% (Petursson et al., 2013). In such a case, a C factor that was calculated with recent remote sensing data would fail to reflect the condition of the vegetation during the monitoring period.

Fig. 8a. In order to improve the clarity of the boxplots in figure 8a, I suggest to eliminate the dots, whose presence is not much effective since the data spread can be derived from the length of the whiskers of the boxplots. A similar consideration holds for fig. 9and S1 and S2 in the supplement material.

From our experience the statistical summary measures illustrated by boxplots strongly reduce the information provided by data and can be misleading with small sample sizes and strongly non-normal distributions. We therefore prefer to also show the data that results in the illustrated boxes.

We preferred to keep all data points in the plots of the figures Fig. 8, Fig. 9, and the figures in the supplementary document.

Technical corrections

Pag 1 line 8: "challanges" should be "challenges" Pag.19 line 32 check the sentence Pag. 26 line 9 replace ULSE with USLE

Thank you. We will revise the misspellings accordingly.

The typos were changed accordingly in the revised version of the manuscript

References

Arnoldus, H. M. J. (1980). An approximation of the rainfall factor in the Universal Soil Loss Equation. An approximation of the rainfall factor in the Universal Soil Loss Equation., 127-132.

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Fenta, A. A., Yasuda, H., Shimizu, K., Haregeweyn, N., Kawai, T., Sultan, D., ... & Belay, A. S. (2017). Spatial distribution and temporal trends of rainfall and erosivity in the Eastern Africa region. Hydrological Processes, 31(25), 4555-4567.

Kinnell, P. I. A. (2010). Event soil loss, runoff and the Universal Soil Loss Equation family of models: A review. *Journal of hydrology*, *385*(1-4), 384-397.

Reply to the reviewer comments RC3: 'referee comments', by Anonymous Referee #3

General comments

This paper presents an analysis of the variability in soil loss estimates with the USLE equation due to different representations of its factors, and subsequent comparison of the predictions with field data. It is certainly not the first time that the uncertainty of erosion predictions with the USLE is questioned. Yet, the fact that the USLE is very often applied using very different data and methods to determine its input factors still make the study relevant. The study uses a representative selection of frequently used methods to determine the USLE factors based on readily available land use climate, soil and topography data. The paper is generally well written, but could be more concise at some points and there are some issues that require better explanation or justification, as explained below.

We would like to thank the Anonymous Referee #3 for the highly detailed review of our study and the constructive comments to improve the quality of the manuscript. We appreciate the positive feedback on the manuscript. In the following, we addressed each comment individually. The reviewer comments are printed in *serif, italic font*. Our replies to the comments are written in black, non serif font. The actual changes in the revised version of the manuscript are outlined in blue non serif font. The cited literature is added at the end of the document.

The authors rightly argue that there is a huge range in erosion rates predicted in function of the methods used to obtain the model input factors. What is interesting however is that the ensemble prediction shows relatively good agreement regarding the predicted erosion severity class. So, although agreement with measured erosion data is poor, in line with earlier studies, you might argue that such ensemble prediction is useful for qualitative description of erosion severity. This can be helpful to prioritize policies.

We appreciate the positive comment. Yet, we think that this perspective on the agreement of the ensemble with respect on soil loss levels is a little too optimistic. Fig. 4 (and particularly panel a)) shows a strong agreement of the model ensemble for soil losses below a threshold of 10 t ha^{-1} yr^{-1} that was defined as “tolerable” soil loss in this study. Thus, the model ensemble is able to identify regions with no or a low erosion risk. In potentially erosion prone areas, however, a large spread is visible in the ensemble prediction of the soil loss classes. This is particularly visible for large parts of the Rift valley and the South-West of Uganda where large ranges from “tolerable” to “high” are visible.
Fig. 5 was intended to support the reader to assess the confidence of the model ensemble to predict a soil loss level. From that perspective we think, however, that the picture that is conveyed by Fig. 5 can be too optimistic and gives the impression of a strong agreement for the areas that were analyzed in detail (see panes c) to d)). Thus, we suggest to revise Fig. 5 to improve the readability of the probability of models in a class in the figure.
Despite the described limitations we think that the argument that the Anonymous referee #3 stresses is highly valuable. Section 5.1 briefly discusses the relevance of the model ensemble to provide information on the confidence to predict the severity of the soil erosion

risk. We suggest, however, to strengthen this argument and add a short paragraph on the potential of a model ensemble to support policy making in Section 5.1.

The suggested section was implemented as section 5. in the revised version of the manuscript.

However, the comparison of predicted soil loss with measured erosion and sediment yield data is most problematic. As the authors also mention at some point, the USLE does not consider sediment deposition and transport so it cannot be compared with sediment yield from gauging stations. On the other hand, the erosion rates provided by De Meyer et al. (2011) based on reconstructing the historic surface level and calculating the lost soil volume from 36 farm compounds are extremely high. I am not sure which method was applied exactly by De Meyer et al and for what time and spatial scale the assessments are made for example. In any case, such high values can occur at certain points, but are probably not realistic for larger areas. So, the question is how useful are these comparisons actually, and do we need them to assess the uncertainty in USLE predictions due to variations in its factors? Model validation is very important,but only useful if the modelled and measured data refer to the same processes and the same scales of assessment.

We fully agree that a comparison of soil loss calculations with USLE type models to in-field data is problematic. We think, however, that it is relevant to illustrate potential issues that arise from a comparison of soil loss calculations to in-field data that may stem from different types of erosion monitorings, simply because it is frequently performed in erosion studies and we think that such common practice must be critically evaluated. As this point was addressed by other referees in a similar way we think that it is relevant to better specify the intention of the model validation as it was performed in this study. We therefore suggest to revise section 3.7 of the manuscript accordingly.

In the revised version of the manuscript we want to emphasize that a comparison must be done with great care due to the differences in the approaches that were employed the soil loss in the field and the processes that are actually considered in the soil loss estimation. Thus, we revised the discussion section on the comparison to in field monitorings (now section 5.4)

I find the classification of the predicted soil loss values in four classes, below and above tolerable soil loss rate of 10 t/ha/yr, problematic and it does not add much to the entire discussion of the uncertainty of model predictions. First of all, the tolerable soil loss rate depends on a spatially variable soil production rate, which is unknown for the area. Secondly, the USLE soil loss predictions are gross erosion rates and do not account for deposition during transport over distances longer than a standardized erosion plot. This makes it highly arguable to look at the USLE predictions in relation to tolerable soil loss rates. You can classify the predictions in erosion severity classes but I recommend to delete reference to tolerable soil loss rates.

Thank you for this advice. We agree that the selected terminology is highly critical, particularly due to the arguments that were stated by the Anonymous referee #3. The term “tolerable” seems to be too specific and implies that process relationships are known that are indeed unknown. We therefore suggest to add a paragraph in section 3.4 to indicate that the actual soil formation rate is unknown, but that we use this threshold as it is frequently used in other literature. We additionally suggest that we change the term “tolerable” to e.g. “slight” in the revised version of the manuscript and indicate that we refrained from using the term “tolerable” due to the above stated issues.

The following paragraph was added in section 3.4:

In this study low soil losses were classified by employing the same threshold. Yet, no information on soil formation was included and thus the term *tolerable* is misleading. Consequently a soil loss between 0 and 10 tons $ha^{-1}yr^{-1}$ is defined as slight soil loss, as suggested by Fenta et al. (2020).

Throughout the revised version of the manuscript the term *slight* is now used instead of *tolerable*.

What exactly is the aim of the comparison of soil loss estimates at the administrative level? How does this contribute to the research objectives explained in the introduction? While it can be an interesting exercise, and may provide relevant information for local policy makers, it seems the whole section 4.3 does not really contribute to the main objectives of your study.

We agree that the analysis of the mean soil loss on an administrative level is not specifically outlined in the introduction. Yet, often erosion studies perform the analysis of the soil loss (or any related measures) for defined administrative units (see e.g. Gourevitch et al. (2016), or Karamage et al. (2017) for districts in Uganda, or Panagos et al. (2015b) for provinces at the NUTS3 level in Europe). In theory one could assume that local disagreements of the model combinations will be reduced by a spatial averaging and as a consequence the input uncertainties are less critical for a soil loss assessment on the administrative level. Yet, the uncertainty analysis on the administrative level shows that large uncertainties are present in the aggregated soil loss estimates. Thus, any decision making based on a single USLE model estimate is highly questionable. The comparison with the results of Karamage et al. (2017) for Ugandan districts clearly illustrates this issue. Therefore, we conclude that the results presented on the administrative level provide essential insights in the evaluation of uncertainties in soil loss estimation. We agree, however, that our intention with the soil loss assessment on the administrative level was not specified well enough. Therefore, we suggest to add a brief section to outline the intention sketched above.

In the revised version of the manuscript we added the comparison to previous studies in the region that employ single USLE models to the research questions.

The focus of the analysis on the administrative level was shifted from the simple analysis of aggregated soil losses towards the analysis of the ensemble soil losses aggregated for different administrative domains and their comparison to studies that calculated the soil loss for the same administrative units. In the revised version of the manuscript an analysis on a national level compares the calculated soil losses to the ones reported in Fenta at al. (2020) additionally to the comparison on the administrative level and the comparison to the results of Karamage et al. (2017) that was already shown in the previous version of the manuscript.

Therefore, the methodology in section 3.6 and the results section 4.3 was revised. A more detailed discussion of the comparison to Fenta et al. (2020) and Karamage et al. (2017) was added in the discussion.

Please explain and illustrate with quantitative data why you did not include the ASTER DEM for calculation of the LS factor. Previous studies have also highlighted that at higher resolutions problems can occur with LS calculations, but since you first projected the ASTER DEM on the 90 SRTM grid could be expected to be less problematic. It would be interesting to see what is exactly the cause of this problem and compare this to other studies that assess the differences in ASTER and SRTM DEMs and their application in erosion studies.

We agree that the found issues with ASTER DEM to calculate the LS factor could be elaborated with more detail. Due to the length of the present manuscript we, however, tried to keep this section concise. We suggest to add a section that illustrates the artefacts in the calculated LS factor realizations using ASTER DEM in the supplementary materials.

We added the Figure and the text below in the supplementary document:

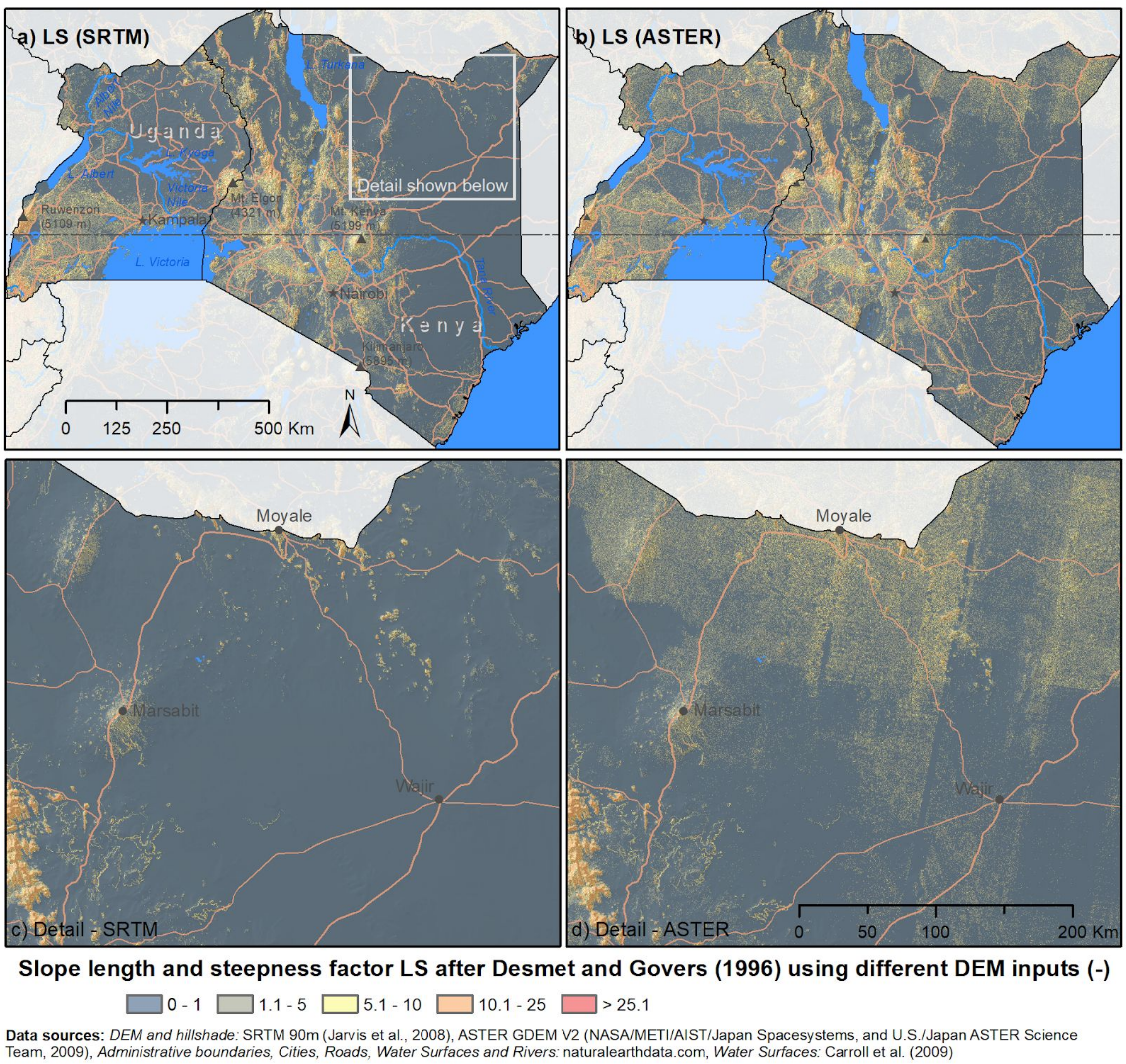

Figure S.1: LS factor realizations that result from SRTM 90m (Jarvis et al., 2008) a) and ASTER DEM (NASA/METI/AIST/Japan Spacesystems, and U.S./Japan ASTER Science Team, 2009) b) when employing the method of Desmet and Govers (1996) for the LS calculation. The map detail indicated in panel a) is shown for SRTM 90m and ASTER DEM in the panels c) and d), respectively. ASTER based calculations show random and systematic noise in the detail in panel d).

As outlined in the main document of this work, the realizations for the LS factor that used ASTER DEM (NASA/METI/AIST/Japan Spacesystems, and U.S./Japan ASTER Science Team, 2009) for their computation were excluded from the analyses as issues were encountered in the simulation results that stem from noise and artefacts in the ASTER DEM inout data. As a result, only three instead of six realizations for the LS factor were used. Fig. S1 shows the LS factor realizations that result from SRTM 90m (Jarvis et al., 2008) and ASTER DEM when employing the method of Desmet and Govers (1996) for the LS calculation. The panels a) and b) show the results for the entire study area. The panels c) and d) show the detail located in the North-East of Kenya. While the LS calculations using the SRTM show low values close to 0 for large regions where the terrain is overall flat, the LS realization that implemented the ASTER DEM shows (i) random, non-systematic noise (the yellow scatters in flat terrain with no noteworthy heterogeneity in landscape) and (ii) systematic errors (strips), which originate from satellite malfunction or issues in data processing. (i) and (ii) can be clearly seen in the detail showing the dry, north-eastern part of Kenya. Based on the identified noise patterns (among other patterns e.g. in northern Uganda, that are not shown in detail here) we decided to exclude the LS realizations that are based on the ASTER DEM from the set of LS realizations that were used in the analyses of the manuscript. Although not illustrated here, other methods to calculate the LS factor showed comparable results and supported the assumption that the visible errors result from the input DEM rather than from the computation method itself.

The methods used to assess the C factor rest strongly on the approach used by Panagos et al (2015) and Borrelli et al (2017), but I find the description quite difficult to follow. It is not clear why and how exactly you overlay the already spatially distributed 'crop shares statistics' with the land cover maps? Moreover, it seems the approach puts a lot of detail in differentiating between different crops, but disregards the possible importance of intra-annual differences in C factors due to crop rotations.

The method to calculate the C factor that was proposed by Panagos et al (2015a) was adopted in several preceding studies (see e.g. Fenta et al. (2020), Batista et al. (2017), Borrelli et al. (2017), Lugato et al. (2016)). The main concept in this manuscript was to employ frequently used methods to compute the USLE input factors. Therefore, it was also relevant to consider the method of Panagos et al. (2015a) as a member in the set of C factor realizations and to follow the C factor calculation as it is described in Panagos et al. (2015).

Further, the options for the computation of the C factor are often limited by a lack of available crop data. (Nationwide) Agricultural statistics are usually not available for every year. As a consequence, data to consider inter-annual variations in crop statistics are usually not available. A typical assumption that is drawn in the calculation of the C factor based on crop statistics is that the available statistical data is a good average value for the entire analyzed time period.

Statistical agricultural data is not spatially distributed but provided aggregated on an administrative level (see e.g. the National Agricultural census data that was implemented in this manuscript). Also the agricultural data that is available from Monfreda et al. is not fully spatially distributed but aggregated with a spatial resolution of 5 minutes.

There are several other papers that also discussed the impacts of USLE factors and structure on outcomes (e.g. Sonneveld and Nearing, 2003) that would be interesting to include in your discussion.

We were not able to identify studies in our literature review that employed similar analyses as the one presented in this manuscript. Thank you for pointing out the study of Sonneveld and Nearing (2003) which we will mention in this manuscript. We suggest to include further relevant literature in the discussion.

In the revised version of the manuscript we added a brief literature review on the implementation of uncertainty and sensitivity analysis to evaluate the soil loss estimates and the impact of the USLE inputs on the soil loss estimates on P4 L2ff

Further, results of the reviewed studies that were summarized in the introduction were included in the discussion section 5.3.

Detailed comments (indicated per Page and Line):

P2-L17-18: can you add a line how the revised version was different?

We will add the following to the sentence on P2 L16-17:

Further data were collected over the following decades and the methods to calculate the USLE input factors were substantially revised. This resulted in an update of the iso-erodent maps, the consideration of seasonality and rock fragments in the K factor, or a consideration of additional sub factors for the computation of the C factor.

We added the suggested sentence in the revised version of the manuscript on P2 L17.

P3-L8-11: you may add here a few words on the often used Sediment Delivery Ratio in combination with gross erosion to obtain sediment yield predictions, correcting for the fact that the USLE does not predict sediment deposition.

We will add a short section that acknowledges approaches that also account for deposition processes and employ the Sediment Delivery Ratio (e.g. Rajbanshi et al. (2020), De Rosa, et al. (2016), or Sharp et al. (2015)).

On P3 L11 we added a sentence to refer to methods that employ e.g. the SDR to compute the sediment delivery from soil loss estimates.

P3-L14: remove 'the'

Will be removed accordingly

‘the’ was removed.

P3-L20-23: please check and preferably simplify this sentence.

We will revise the sentence on P3 L20-23 as follows:

The implemented remote sensing data products describe (or are a proxy for) features in the landscape (e.g. a DEM represent the topography and the NDVI is often employed to describe vegetation density). In large scale assessments methods are implemented that employ these large scale data products to infer spatially distributed estimates for the USLE inputs.

The sentence on P3 L20-23 was replaced by the suggested sentence in the revised version of the manuscript.

P3-L33-35: It is indeed not simple to do this kind of comparisons and most plot data do not cover 20 years, but there are by now relatively good and large datasets of measured soil loss available, such as for example the data presented by Garcia Ruiz et al (2015)and Maetens et al. (2012) for Europe. For many other parts of the world this is stillmore difficult though.

We agree. Observation data that was collected by García-Ruiz et al. (2015) in their comprehensive meta-analysis was implemented in the present manuscript to compare the soil loss estimates with. Nevertheless, this is one argument that we wanted to stress with this study, that although such data exists a comparison is not always feasible.

We suggest to additionally mention these data sets on P4 L1 in the following:

Large scale meta-analysis studies of soil erosion plot data and sediment yield records exist, such as García-Ruiz et al. (2015) globally, Vanmaercke et al. (2014) for Africa, or Meatens et al. (2012) for Europe.

We added the suggested sentence on P4 L1 in the revised version of the manuscript.

P4-L10: Research objectives are now formulated as research questions; better write them as objectives. In the last objective correct ‘we we’.

We think that this is a question of style and preference and would prefer to keep the research questions. We will remove the second ‘we’.

We kept the research objectives formulated as questions. The second ‘we’ was removed.

P4-L16-24: These lines do not seem necessary, and seem repetitive.

We agree that this paragraph does not provide any new information, but outlines the structure of the manuscript. We think that this is a subjective question of style and preference and believe that it helps the reader to get an overview of the content of the paper at hand.

We preferred to keep this section in the revised version of the manuscript.

P5-L4: on the steepest slopes (>20) gully erosion can be expected to be an issue as well.

We cannot identify where this statement applies in the text.

We realized, that anonymous referee #3 was referring to the figure legend. Yet, we would prefer to keep this classification, as it shows the classification that was done by Ebisemiju (1988)

P7-L6: what about seasonality of rainfall?

As discussed in another reply to the comments by the Anonymous referee #2 we argued that the measures such as the Modified Fournier Index (MFI, Arnoldus, 1980) can provide valuable information to characterize the seasonality of the rainfall erosivity. Therefore, we suggest to calculate the MFI for the study region and analyze the spatial pattern. If the shown patterns strongly differ from the patterns of the shown long-term annual precipitation we suggest to add a panel to additionally show the MFI in Fig.1.

The rainfall seasonality is now considered in the revised version of the manuscript as follows:

In Fig. 1 an additional plot panel was included showing the Seasonality Index (SI; Walsh and Lawler, 1981), as a measure for the seasonality of the rainfall.

The set of realizations for the rainfall erosivity R now includes two additional realizations that were presented in Fenta et al. (2017) where one method employs long-term mean annual precipitation to calculate R and the second method uses the MFI to account for the seasonality of the rainfall. Fenta et al. (2017) applied both methods in a large scale study in Eastern Africa. As a result 972 realizations of the USLE model are analyzed in the revised version of the manuscript, compared to the 756 realizations that were presented in the previous version of the manuscript.

P8-L8 and supplementary Table S1: It seems you only used relationships based on mean annual precipitation to estimate the R factor (not accounting for seasonality). It would have been interesting to include an equation based on the monthly data, for example those based on the Modified Fournier Index proposed by Renard & Freimund(1994) that you cite. The text above Table S1 states ‘The ï˘n ¸Arst four methods’ which should be the ‘first five’.

The simple reason why primarily long-term annual precipitation was implemented to calculate the rainfall erosivity factor, was that the literature on large scale soil loss assessments as well implemented primarily long-term annual precipitation products to calculate the rainfall erosivity. We agree that a comparison of long-term annual precipitation to the MFI can provide valuable insight. We suggest to apply the MFI (Arnoldus, 1980) for the study region and compare the results with long-term annual precipitation to put it into reference. We suggest to add any analysis in the supplementary materials.

We will change ‘first four’ to ‘first five’ in the text above Table S1.

Please see the comment above how rainfall seasonality is accounted for in the revised version of the manuscript.

Due to the additions in the R factor input set, the section in the supplementary document was substantially revised.

Supplementary page 8 (above table S6) correct 'To compute the K factor realizations..'for 'To compute the LS factor realizations'.

Thank you. This will be changed accordingly.

This was changed accordingly.

P9L30: please correct sentence 'served as base layers for the join with..'

P9 L29 - L31 will be modified as follows:

Two land cover products, the MODIS Collection 5 LC with a spatial resolution of 250m (Channan et al., 2014; Friedl et al., 2010) and the ESA CCI LC Map v2.0.7 with a spatial resolution of 300m (ESA, 2017) served as base land cover layers. The agricultural, forest, and naturally vegetated land cover in these maps were superimposed with C factor literature values. The C factor values for agricultural land uses were calculated based on agricultural statistics.

The sentence on P9 L29ff was replaced with the suggested sentence in the revised version of the manuscript.

Table S7: what does the first column 'value' mean?

The value represents the crop group ID which is the same as in the following table. Therefore, the column name "value" will be changed to "Group ID" in the tables S.7 and S.8

The column names in the tables S.7 and S.8 were changed accordingly.

P12-L16: this may be interesting, but where exactly do we find the results of this? I couldn't find it in the results section.

The calculated values for the sensitivity index for all four USLE inputs was used to rank the inputs. Therefore, the calculated sensitivities values are not shown. Due to the length of the manuscript we decided to only keep Fig. 6 that shows the most dominant input in each grid cell. We suggest to add a figure that shows the sensitivity indices for all four USLE inputs in the supplementary materials.

The following figure was added in the supplementary document:

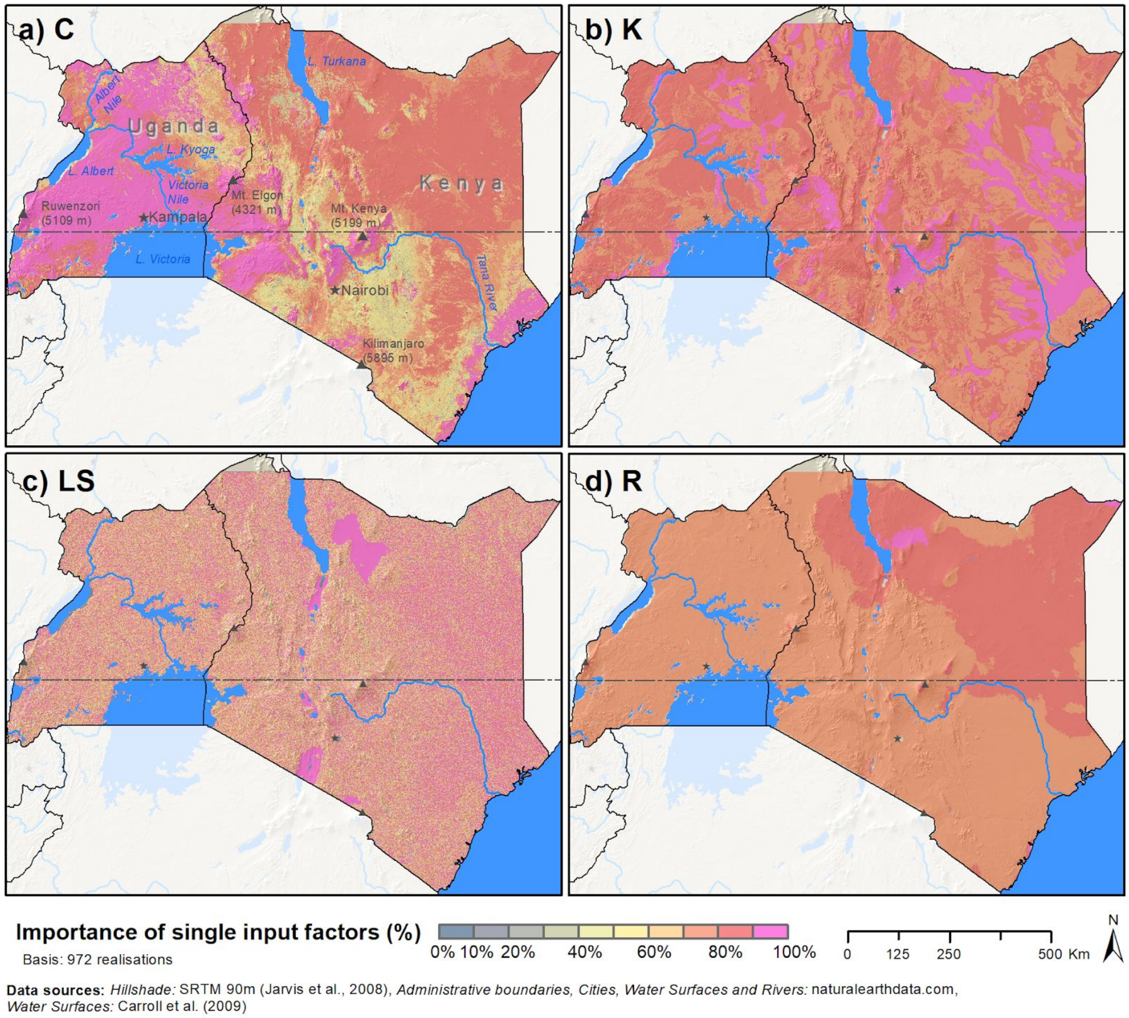

Figure S.4: Results for the sensitivity index calculated for all four USLE input factors.

P12-L19: it is not clear from this paragraph how the comparison of soil loss rates at the administrative level contributes to the papers objectives expressed in the introduction.

Please see our reply to the comment on the analysis of soil loss on the administrative level above.

P14-L29: With 'the dominant soil loss levels that a majority of model setups predicted' you refer to the soil loss level for which most agreement was between the model setups? What if there was no majority for any of the soil loss levels? Unfortunately, in the figure 5, the lightness of the colours that should indicate the percentage of models that calculated a soil loss within the respective soil loss classes, cannot be distinguished.

Numerically there should be a dominant input when we apply Eq. 4 to calculate the sensitivities. The only exception is when several inputs are 0 and therefore both inputs have a sensitivity of 1. This should however not be the case as no input is exactly 0 in any grid cell. Nevertheless, we agree that Fig. 6 does not show if two inputs are almost equally

relevant. Therefore, we suggest to add a figure that shows the individual sensitivity indices in the supplementary document as suggested above.
Further, we try to improve the readability of Fig. 5 to better distinguish between the percentages of agreement.

We tried to improve the readability of Fig. 5 by reducing to only two classes (0-50% and 50-100% of the models that agree on a soil loss level) that indicate the model ensemble agreement.

Figure 7: in the heading it states that the values refer to those pixels for which 'high to severe soil loss was predicted to be likely'. How is 'to be likely' defined here? Or does this refer to high or severe soil loss as predicted per model implementation?

This sentence in the figure caption will be changed to:
The cases A) to D) include the values of input factor realizations for grid cells, in which the respective input factor was the most sensitive one and the majority of models of the model ensemble predicted high to severe soil loss.

The sentence in the figure caption of Fig. 7 was replaced accordingly.

P20-L20: why do you highlight and compare with the data from Karamage et a (2017)? Did you introduce this in methods? I don't see the added value, especially considering that the data are already covered within your model implementations, so it seems there is nothing new.

Karamage et al. (2017) performed a soil loss assessment for the districts of Uganda. Therefore, a comparison of the model ensemble that we have calculated to their results can be easily performed. The comparison to the results of Karamage et al. (2017) is relevant, because it illustrates the central issue with soil erosion studies that we want to address in this manuscript. Karamage et al. (2017) implemented a single USLE model setup. The comparison with the model ensemble highlights that the USLE input combination that was implemented in Karamage et al. (2017) results in soil loss estimates that are in some cases even lower than the interquartile range that is provided by the USLE model ensemble. When single USLE model setups are implemented in erosion studies this information is simply not available.

P23-L18: But you did not really perform a plausibility check of the individual USLE model realisations, so the argument does not make too much sense.

We admit that the individual generated input realizations were not analyzed for plausibility. All of the implemented methods were however implemented in previous peer reviewed studies that had similar study settings. Therefore, we considered all or the implemented methods as potential methods to compute the USLE input factors.
We agree that this statement implies that we thoroughly checked all input realizations for plausibility. Thus, we suggest to remove this statement.

This paragraph was completely revised and this statement is removed.

P24-L8: the comparison with one particular study does not contribute anything to this interpretation; the wide variety between your results indicates that you cannot take conclusions based on only 1 model implementation and that an ensemble approach makes more sense.

We provide the comparison to the study of Karamage et al. (2017) as an example here that describes, however, a general problem. In principle P24 L8-L10 supports the statement outlined by the Anonymous referee #3.

P24-L15-18: This sentence misses a conclusive statement. Indeed, the tolerable soil loss is controversial and does not seem to add much to your assessment.

We will add the following statement:

The terms that represent certain ranges of soil loss, such as “tolerable”, or “moderate” must therefore be interpreted carefully.

The proposed statement was added accordingly.

P24-L26-27: please correct this sentence.

The sentence will be revised accordingly:

Fig. 6 illustrated the most dominant USLE input factor realizations with respect to their impact on the uncertainties of the calculated soil loss. The dominant input factors revealed spatial patterns on different spatial scales.

The sentence on P20 L26-27 was replaced by the proposed sentence accordingly.

P24-L28-20. The detail in the patterns is not a property of the factor, or how important the factor is, but it just reflects the level of spatial variability that is present in the input data used. This does not mean anything for the relevance of one factor as compared to another or a scale influence. The interesting part of your result is the overall impact of each factor on total ensemble variability.

We do not fully agree with this statement. Yes, the patterns which are shown in Fig. 6 are not a property of the input factors. The patterns are however a result of the variability of the input factor realizations in each grid cell. In each grid cell the analysis that is illustrated in Fig.6 assesses the uncertainty range in the calculated soil loss that is caused by each set of input realizations for the four analyzed USLE inputs and shows the input with the largest impact. If neighboring pixels form a spatial pattern then we can assume that the employed methods to compute the respective input strongly disagree. This insight can help to understand what the dominant source for the simulation uncertainties are locally. We fully agree with the statement that the shown patterns follow the patterns that are given in the used input data that are combined with the methods to calculate the USLE input factors. But that is exactly what we want to analyze with this figure.

We will revise the sentence to specify the statement accordingly:

The patterns of the most dominant inputs follow the patterns of the input data that were employed to calculate the input factor realizations. Thus, the shown patterns can support in identifying the input data/method combination that introduced the largest share of uncertainties in the calculation of soil loss locally.

The sentence on P24 L28ff was replaced by the suggested sentence accordingly.

P25-L11: at larger spatial scales you will need to include not only different sources of sediment (rill, gullies, mass movements), but also deposition during transport, as explained in detail by numerous previous studies.

We will add the following statement:

At larger scales, processes other than the ones that are assessed by the USLE, such as deposition processes, gully erosion, or bank collapses have to be considered in the quantification of the soil loss (Govers, 2011).

The proposed sentence was included on P25 L11 in the revised version of the manuscript.

P25-L20: If the data are in stream sediment loads they are certainly do not 'better meet the spatial scale of USLE'.

We agree. The statement will be revised accordingly:

Other reference studies, such as Sutherland and Bryan (1990) or Kithiia (1997) represent the average soil loss at the catchment scale. One could assume that the spatial scale of such studies better agrees with the spatial scale of a large scale soil loss assessment with the USLE.

We revised the sentence on P25 L19 accordingly.

P25-L26-28: Various studies have dealt in detail with the role of spatial scale in erosion assessments, and how plot scale data compare to sediment yield (e.g. de Vente et al,2007). Further, the difference between the plot data and USLE model predictions do not have anything to do with comparing plot data with landscape scale sediment yield. Plot data and the USLE assessments in theory both consider the same erosion and deposition processes at the same scale.

Thank you for addressing this article. We suggest to include the findings of this work (and others e.g. Sidle et al. (2017)) in the discussion on P25 as it contributes to provide a more differentiated view on the comparison of in-field data to our model ensemble calculations.

P25-L31-33: I think quantitative validation via google earth will be difficult and you do not really explain how this could be done.

It was not our intention to provide new approaches for a USLE model evaluation in this manuscript. The key message was that model evaluation as it is frequently done is strongly limited due to the arguments that we have stated in the discussion. Yet, we wanted to indicate that we have to think of other potential options to evaluate soil loss estimates and simply provided the method described in Bosco et al. (2014) as an example.

P26-L9: ULSE = USLE

This will be changed accordingly.

The typo was changed accordingly.

P26-L12-14: computer capacity for these kind of calculations should nowadays for most studies not be a problem anymore.

Our analyses were indeed limited by the computational resources that were available at our Institute, at least when time resources are taken into account as well. Adding additional input factor realizations would not have been feasible with our available resources, as the required storage capacities would easily have exceeded 50+ TB.

Based on our reply we kept the statement on P26 L12-14 in the previous version of the manuscript also in the revised version of the manuscript, as particularly RAM storage can be a limiting factor in such a study design when employed in large scale applications.

P26-L14: Ideally yes, like in any model you need to validate the predictions. But, how do you determine the plausibility if you don't have field data to compare with? Based on your assessment and comparison with field data would you say that the USLE assessments are plausible? You need data that can be compared with the USLE predictions, so representative for the same scale. I think the main interest is in the fact that the ensemble prediction shows relatively good agreement in the severity class of erosion, but quantitative validations are problematic.

We agree that the statement on P26 L14 misses a clear argument on how to check the plausibility. We think that it overall does not contribute much to the paragraph. Thus, we suggest to delete this sentence.

The sentence: "Nevertheless, checking the plausibility of estimated soil loss must be the minimum requirement for every study employing the USLE (see suggestion above and Bosco et al., 2015, 2014)." was deleted accordingly.

P27-L4: please rephrase and simplify the sentence.

Will be rephrased as follows:

We generated sets of realizations for each USLE input factor and combined them to 756 USLE model setups to compute spatially distributed soil loss estimates for Kenya and Uganda. Based on the generated USLE model combinations we analyzed and quantified the impacts of frequently used methods to calculate USLE inputs on the uncertainties in the soil loss estimation with the USLE model.

We replaced the sentence on P27 L2-5 in the previous version of the manuscript with the paragraph suggested above.

P27-L11: increased soil loss = high soil loss

This will be changed accordingly.

We rephrased accordingly.

P27-L26-28: Most important here is to make sure that the data are comparable, so representing the same erosion and sediment transport or deposition processes. In theory, USLE predictions should compare with plot data.

We agree that in theory this statement is true. Yet, it assumes that the employed USLE model was properly parameterized and that the used in-field data stems from a long-term plot experiment. Both assumptions might not hold in the presented study setting.

Based on our analyses we still cannot confirm the applicability of plot scale data to be employed as a reference in large scale studies. We replaced the sentence on P27 L26-28 in the previous version of the manuscript with the paragraph suggested below.

P27-L28: this recommendation is very vague. What kind of new approaches? How would google maps provide quantitative estimates that can be compared with model predictions?

We agree that the wording is too vague. We suggest to rephrase to:

We further question the aptitude of soil loss assessments based on in-stream sediment yields or small scale plot experiments to be valid data for the evaluation of soil loss estimates. We should think of new approaches to validate soil loss estimates that employ large scale data that is now available. Bosco et al. (2014) outline a method to employ satellite imagery to check the plausibility of large scale soil loss assessments.

We replaced the sentence on P27 L26-28 in the previous version of the manuscript with the paragraph suggested above.

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Markup document that shows the differences between the first revision and the revised version of the manuscript:

A systematic assessment of uncertainties in large scale soil loss estimation from different representations of USLE input factors - A case study for Kenya and Uganda

Christoph Schürz[1], Bano Mehdi[1,2], Jens Kiesel[3,4], Karsten Schulz[1], and Mathew Herrnegger[1]

[1]Institute for Hydrology and Water Management, University of Natural Resources and Life Sciences, Vienna (BOKU), Vienna, Austria

[2]Institute of Agronomy, University of Natural Resources and Life Sciences, Vienna (BOKU), Tulln, Austria

[3]Leibniz Institute of Freshwater Ecology and Inland Fisheries (IGB), Berlin, Germany

[4]Institute of Natural Resource Conservation, Department of Hydrology and Water Resources Management, Christian Albrechts University of Kiel, Kiel, Germany

Correspondence: Christoph Schürz (christoph.schuerz@boku.ac.at); Mathew Herrnegger (mathew.herrnegger@boku.ac.at)

Abstract. The Universal Soil Loss Equation (USLE) is the most commonly used model to assess soil erosion by water. The model equation quantifies long-term average annual soil loss as a product of the rainfall erosivity R, soil erodibility K, slope length and steepness LS , soil cover C and support measures P. A large variety of methods exist to derive these model inputs from readily available data. However, the estimated values of a respective model input can strongly differ when employing different methods and can eventually introduce large uncertainties in the estimated soil loss. The potential to evaluate soil loss estimates at a large scale are very limited, due to scarce in-field observations and their comparability to long-term soil estimates. In this work we addressed (i) the uncertainties in the soil loss estimates that can potentially be introduced by different representations of the USLE input factors and (ii) ~~challanges~~ challenges that can arise in the evaluation of uncertain soil loss estimates with observed data.

In a systematic analysis we developed different representations of USLE inputs for the study domain of Kenya and Uganda. All combinations of the generated USLE inputs resulted in ~~756~~ 972 USLE model setups. We assessed the resulting distributions in soil loss, both spatially distributed and on the administrative level for Kenya and Uganda. In a sensitivity analysis we analyzed the contributions of the USLE model inputs to the ranges in soil loss and analyzed their spatial patterns. We compared the calculated USLE ensemble soil estimates to available in-field data and other study results and addressed possibilities and limitations of the USLE model evaluation.

The USLE model ensemble resulted in wide ranges of estimated soil loss, exceeding the mean soil loss by over an order of magnitude particularly in hilly topographies. The study implies that a soil loss assessment with the USLE is highly uncertain and strongly depends on the realizations of the model input factors. The employed sensitivity analysis enabled us to identify spatial patterns in the importance of the USLE input factors. The C and K factors showed large scale patterns of importance in the densely vegetated part of Uganda and the dry north of Kenya, respectively, while LS was relevant in small scale heterogeneous patterns. Major challenges for the evaluation of the estimated soil losses with in-field data were due to spatial and

temporal limitations of the observation data, but also due to measured soil losses describing processes that are different to the ones that are represented by the USLE.

1 Introduction

The Universal Soil Loss Equation (USLE, Wischmeier and Smith, 1965, 1987) formulates the most commonly applied concept to assess soil loss by water erosion (Alewell et al., 2019; Borrelli et al., 2017; Panagos et al., 2015e; Kinnell, 2010). The USLE is an empirical relationship that computes long-term average annual soil loss as a product of six input factors that characterize the erosive forces of the rainfall (R), the soil erodibility (K), topography (L and S), plant cover (C), and support practices to mitigate erosion (P). Historically, the USLE succeeded earlier attempts to quantify soil erosion by water developed for the Corn Belt region of the United States of America (USA) in the 1940s. First relationships between soil loss on cropland and topography (Zingg, 1940), factors for crops and conservation practices (Smith, 1941), soil erodibility (Browning et al., 1947), and rainfall (Musgrave, 1947) were developed and reported by Wischmeier and Smith (1965). Over several decades extensive soil erosion data were collected in many locations on field plot scale in the USA. Eventually more than 10000 plot-years of field data were analyzed with reference to a "unit plot" to formulate a generally applicable approach for soil loss estimation in the USA (Wischmeier and Smith, 1965; Kinnell, 2010; Renard et al., 2011). The new approach overcame restrictions of previous methods for soil loss estimation to specific regions in the USA and thus was termed "universal" in the literature (Wischmeier and Smith, 1965). Further data were collected over the following decades and the methods to calculate the USLE input factors were substantially revised (Renard et al., 1991, 1997; Govers, 2011). This resulted in an update of the iso-erodent maps, the consideration of seasonality and rock fragments in the K factor, or a consideration of additional sub factors, such as prior land use, for the computation of the C factor (Renard et al., 1997). The revised model was termed as the Revised USLE (RUSLE, Renard et al., 1991). Yet, the general structure of the equation remained unchanged.

In the following we refer to USLE or RUSLE type models as USLE for simplicity. The different revisions of the USLE were summarized in Agriculture Handbooks (Wischmeier and Smith, 1965, 1987; Renard et al., 1997) that proved to be pragmatic and effective tools for soil conservation planning in the USA (Renard et al., 1991, 2011). Not without causing controversies, applications of the USLE model were extended to other land uses than cropland (Renard et al., 1991; Alewell et al., 2019), such as rangeland (Spaeth et al., 2003; Weltz et al., 1998), or woodland (Dissmeyer and Foster, 1980). Due to the principally simple implementation of the USLE model it found a wide application outside of the USA in more than 100 countries (Alewell et al., 2019) at various spatial scales and in various geoclimatic regions (Benavidez et al., 2018). Several studies adopted the methods to calculate the USLE input factors to meet local or regional conditions (e.g., Roose, 1975; Moore, 1979; Bollinne, 1985; Favis-Mortlock, 1998; Angima et al., 2003). Yet, to coin this empirical relationship as being "universal" is misleading for applications outside the USA and to non cropland (Jetten and Favis-Mortlock, 2006). The application of the USLE to conditions different from the plot experiments must be treated as a model extrapolation that is not supported by field data (Bosco et al., 2015; Favis-Mortlock, 1998).

It is well accepted that the USLE does not at all attempt to represent the physical processes to erode and transport soil particles, but rather empirically relates field properties to long term soil loss (Beven and Brazier, 2011; Kinnell, 2010). The USLEs' wide application does not distinguish it to be the best, or only option for soil loss estimation (Evans and Boardman, 2016a). Limitations of the USLE (but also other soil erosion models) have been well documented in the literature (see e.g. Boardman, 1996, 2006). Jetten and Favis-Mortlock (2006) summarize applications of the USLE in Europe, where the validation of calculated soil losses with observed data showed poor results (e.g., Favis-Mortlock, 1998; Bollinne, 1985). Nearing (1998) found that in general soil erosion models tend to over-predict small soil losses and under-predict large soil losses. Kinnell (2010) reports a good performance of a locally adapted variant of the USLE in New South Wales, Australia, but documents the over-prediction of small soil losses and under-prediction of large soil losses when applied to larger domains with a higher variability in agricultural systems (Tiwari et al., 2000; Risse et al., 1993). A recent pan-European soil loss assessment started a broad discussion of the validity of the estimates when compared to in-field soil loss assessments in Great Britain (see the discussion in Panagos et al., 2015e; Evans and Boardman, 2016a; Panagos et al., 2016; Evans and Boardman, 2016b). Several authors question the applicability of the plot scale based USLE to the landscape scale (e.g., Boardman, 2006; Evans, 1995; Govers, 2011), particularly as in large domains other processes such as gully erosion, bank erosion, or sediment deposition can dominate the erosion response (Govers, 2011). Multiple approaches are available from the literature that account, for instance, for the deposition of eroded material by employing concepts such as the sediment delivery ratio (e.g. Rajbanshi and Bhattacharya, 2020; Ferro and Minacapilli, 1995; Graham, 1975). While the USLE principally only accounts for the soil removal and does not consider soil deposition, Evans (2013) concludes that the USLE can be helpful to identify the erosion potential or erosion hot spots, but fails to predict the exact magnitude of ~~erosion~~soil that is eroded.

The above criticism does not impede the wide application of the USLE. For large scale erosion assessments, the availability of large scale spatial data and methods to ~~the~~ infer the USLE inputs facilitate its implementation in GIS (Govers, 2011) and therefore is an attractive option to assess soil erosion. The implementation of remote sensing (satellite) products advances large scale soil loss assessments, particularly in data scarce regions where observations are limited as well as in large domains where in-field data acquisition is infeasible (Alewell et al., 2019; Bosco et al., 2015). This procedure yielded several continental and global estimates of USLE input factors (e.g., Panagos et al., 2017, 2015a, b, c; Vrieling et al., 2010) and soil loss assessments (e.g., Borrelli et al., 2017; Panagos et al., 2015e; Naipal et al., 2015; Yang et al., 2003; Van der Knijff et al., 2000) that were primarily derived from large scale (remote sensing) data products. The ~~methods to compute realizations for the USLE inputs that were proposed in these (and other) large scale assessments attempt to employ data products that~~ implemented remote sensing data products describe (or are a proxy for) features in the landscape (~~such as topography , or vegetation cover)~~e.g. a DEM represent the topography and the NDVI is often employed to describe vegetation density). In large scale assessments, methods are implemented that employ these large scale data products to infer spatially distributed estimates for the USLE inputs. For each USLE input, various methods exist to generate the spatially distributed estimates for the USLE inputs that use different data sources (see e.g. the review of Benavidez et al., 2018). Thus, differing results in the realizations of a USLE input factor can ~~follow~~ result from the different computational approaches. However, a typical setup of the USLE combines only one representation of each USLE input in a single model setup and therefore does not depict the variations in the soil loss calculations that may arise from different representations of the USLE input factors. ~~Very few studies consider the impact of the different representations of the ULSE inputs (e.g., Bosco et al., 2015) to account for the resulting ranges in calculated soil loss.~~ Because of the multiplicative structure of the USLE, uncertainties in the input factors are decisive for the computation of the soil loss as they are ~~also~~ propagated by multiplication (Sonneveld and Nearing, 2003).

Few studies have been conducted to analyze the uncertainties of the calculated soil loss and the sensitivities of soil loss estimates to the USLE input factors. Based on the original USLE data set Risse et al. (1993) performed a comprehensive study to assess the errors in the USLE estimates, evaluated the models' performance to calculate soil loss, and analyzed the influence of the USLE inputs on the model efficiency. Risse et al. (1993) identified the LS factor and the C factor as the most influential inputs. In a meta model study Keyzer and Sonneveld (1997) found that large errors in the soil loss estimates can be expected for high R and LS values, as well as for high and low values for the K factor due to low observation densities in these ranges for these input factors in the original USLE data. Continuing the work of Keyzer and Sonneveld (1997), Sonneveld and Nearing (2003) analyzed the robustness of the USLE model based on different subsets of the original USLE data set and found that the USLE model is not very robust. Falk et al. (2010) employed Bayesian melding to quantify the uncertainties in the soil loss estimates and to identify the USLE inputs that contribute the most to the uncertainties for a catchment in Eastern Australia. In their case study Falk et al. (2010) identified the LS factor to be the most influential USLE input. Based on nine nation wide soil loss data sets, including soil loss estimates for Europe (Panagos et al., 2015e) , and the original USLE data set for the USA Estrada-Carmona et al. (2017) performed global sensitivity analysis to identify the dominant USLE input factors. For all nine countries Estrada-Carmona et al. (2017) found that the C factor and the LS factor were the most influential USLE inputs. Bosco et al. (2015) proposed a multi RUSLE model approach to account for the uncertainties in their soil loss estimates and therefore involve the impact of the different representations of the USLE inputs on soil loss estimation.

A widely applied procedure in environmental modelling to gain confidence in a model setup is model validation, which is the evaluation of calculated model outputs against observed data (Beven and Young, 2013; Young, 2001). Beven and Young (2013) further stress the importance of model falsification when a model fails to reproduce observations. For large scale soil loss assessments the possibilities to evaluate calculated soil losses, or spatially distributed estimates of the USLE inputs are very limited (Bosco et al., 2015; Van der Knijff et al., 2000). Typically, studies that monitored soil loss within the study domain rarely exist. Existing in-field data, however, entail issues of their spatial and temporal representativeness (Evans, 2013; Govers, 2011). Large scale meta-analysis studies of soil erosion plot data and sediment yield records exist, such as García-Ruiz et al. (2015) , Vanmaercke et al. (2014) for Africa, or Maetens et al. (2012) for Europe. Yet, Boardman (2006) questions the comparability of erosion plot data or in-stream sediment yields with soil losses at the catchment scale. Govers (2011) highlights that USLE estimates reflect long time periods (Wischmeier and Smith (1965) e.g. recommended 20 years). Such time periods are usually not covered by a soil loss monitoring campaign. Eventually, USLE input factor estimates and large scale soil loss assessments are compared to very limited observation data (e.g., Borrelli et al., 2017; Vrieling et al., 2010; Moore, 1979) and in many cases no validation was carried out at all (e.g., Karamage et al., 2017; Van der Knijff et al., 2000).

Acknowledging that soil loss assessments using the USLE is uncertain and that the evaluation of soil loss estimates in large scale assessments has limitations, we formulate and systematically address the following objectives:

i. What are the uncertainties in soil loss estimates that we can expect from the implementation of different model input realizations in the USLE model? How can we interpret uncertain soil loss estimates?

ii. Which USLE model inputs contribute the most to the uncertainties of the soil loss estimates?

iii. ~~Can we we~~ How do the USLE ensemble model results compare to other single model studies?

iv. Can we compare the calculated soil loss estimates to in-field soil loss data? Does the evaluation enable us to reduce the uncertainties in the estimated soil losses?

We addressed these questions in a large scale soil loss assessment for Kenya and Uganda and structured our work in the following way: We reviewed methods to calculate USLE inputs that were widely used in previous large scale soil loss assessments and employed selected methods to generate spatially distributed estimates for the study domain (see section 3.2). All combinations of the input factor realizations delineate a USLE model ensemble. The analysis of the USLE ensemble results is outlined in the sections 3.4, ~~4.1, and ??~~and 4.1. We analyzed the impact of the USLE input factors R, LS, K, and C on the calculated ranges of the soil loss estimates in a spatial analysis (see sections 3.5, 4.2, and ~~??). For~~ 5.3). On the national level and for selected erosion prone counties of Kenya and districts of Uganda, we analyze the spatially aggregated mean soil loss estimates and compare them to the results of Fenta et al. (2020) on a national level and to the results of Karamage et al. (2017) on the administrative level for Uganda ~~in Karamage et al. (2017)~~ (sections 4.3 and ~~??~~5.1). In a final step we ~~selected in-field erosion studies that were conducted in Kenya and Uganda and compare the reported in-field erosion data to the~~ compare the ensemble soil loss estimates derived with the USLE model ensemble to selected in-field erosion studies that were conducted in Kenya and Uganda (sections 4.4 and 5.4)

2 Study Area

The study area covers the countries of Kenya and Uganda, located in East Africa (Fig. 1). Overall the Sub-Saharan countries experienced drastic land degradation and a decrease in net-primary productivity of the land over the last decades (Bai et al., 2008). The dominant driver for land degradation in the horn of Africa is soil erosion by water (Jones et al., 2013). Large parts of Kenya and Uganda are generally prone to soil loss by water induced erosion.

In total, the study region covers an area of 821405 km^2, of which 729622 km^2 or 89 $\%$ of the surface are analyzed, since lakes and other water bodies are excluded from the analysis. Additionally, 27 administrative units in both countries (Fig. 1a), Table 1) are analysed in detail. The selection of the erosion prone administrative units is based on a visual analysis of Fig. 1a) and on local knowledge and on-site experience.

The study region covers a wide range of factors influencing soil erosion. Fig. 1a) shows the potential erosion risk solely stemming from topography, based on thresholds suggested by Ebisemiju (1988). Large areas with moderate to steep slopes

Table 1. Administrative units analysed in more detail. The locations are shown in Fig. 1a). The slope and elevation statistics are based on SRTM v4.1 90m DEM (Jarvis et al., 2008).

Nr.	Country	Greater Region	Administrative unit	Area (km^2)	Mean slope (deg)	Max. slope (deg)	Mean elev. (m)	Max. elev. (m)	Min. elev. (m)
1	Uganda	-	Kiruhura	4636	4.39	28.96	1310	1670	1178
2	Uganda	Lake Bunyoni	Ntungamo	2062	7.57	43.61	1497	2224	1279
3	Uganda	Lake Bunyoni	Kabale	1740	14.79	46.15	1990	2601	1355
4	Uganda	Lake Bunyoni	Kisoro	733	11.95	49.44	1983	3861	1338
5	Uganda	Lake Bunyoni	Kanungu	1335	8.61	46.52	1388	2499	912
6	Uganda	Ruwenzori	Kasese	3402	8.81	60.54	1493	5034	878
7	Uganda	Ruwenzori	Kabarole	1825	8.01	48.94	1515	3996	626
8	Uganda	Ruwenzori	Bundibugyo	2265	5.65	52.24	1002	4659	612
9	Uganda	-	Nebbi	2922	3.71	34.70	1039	1873	612
10	Uganda	-	Kaabong	7301	5.87	61.41	1416	2720	834
11	Uganda	Mt. Elgon	Bukwo	529	12.28	53.35	2420	4204	1253
12	Uganda	Mt. Elgon	Kapchorwa	1215	8.00	53.39	1823	4265	1062
13	Uganda	Mt. Elgon	Sironko	1106	7.15	60.43	1619	4280	1045
14	Uganda	Mt. Elgon	Bududa	253	16.99	61.70	2103	4314	1216
15	Uganda	Mt. Elgon	Mbale	522	5.50	71.23	1288	2351	1083
16	Uganda	Mt. Elgon	Manafwa	606	8.34	57.77	1608	3319	1139
17	Kenya	Mt. Elgon	Bungoma	3036	5.15	45.12	1859	4304	1213
18	Kenya	S-W Kenya	Kisii	1353	6.24	32.83	1750	2190	1394
19	Kenya	S-W Kenya	Nyamira	897	6.70	31.99	1888	2214	1509
20	Kenya	S-W Kenya	Bomet	2384	5.14	30.29	1997	2465	1693
21	Kenya	Cherangani Hills	Elgeyo-Marakwet	3058	9.97	60.70	2122	3517	920
22	Kenya	Cherangani Hills	West Pokot	9328	8.70	67.15	1443	3524	691
23	Kenya	-	Samburu	21250	6.81	66.83	1185	2834	296
24	Kenya	Mt. Kenya	Nyeri	3380	7.39	54.88	2284	5035	1210
25	Kenya	Mt. Kenya	Kirinyaga	1491	4.41	45.27	1619	4747	1057
26	Kenya	Mt. Kenya	Embu	2780	4.89	38.56	1191	4760	520
27	Kenya	-	Makueni	8297	3.84	58.42	1065	2120	404

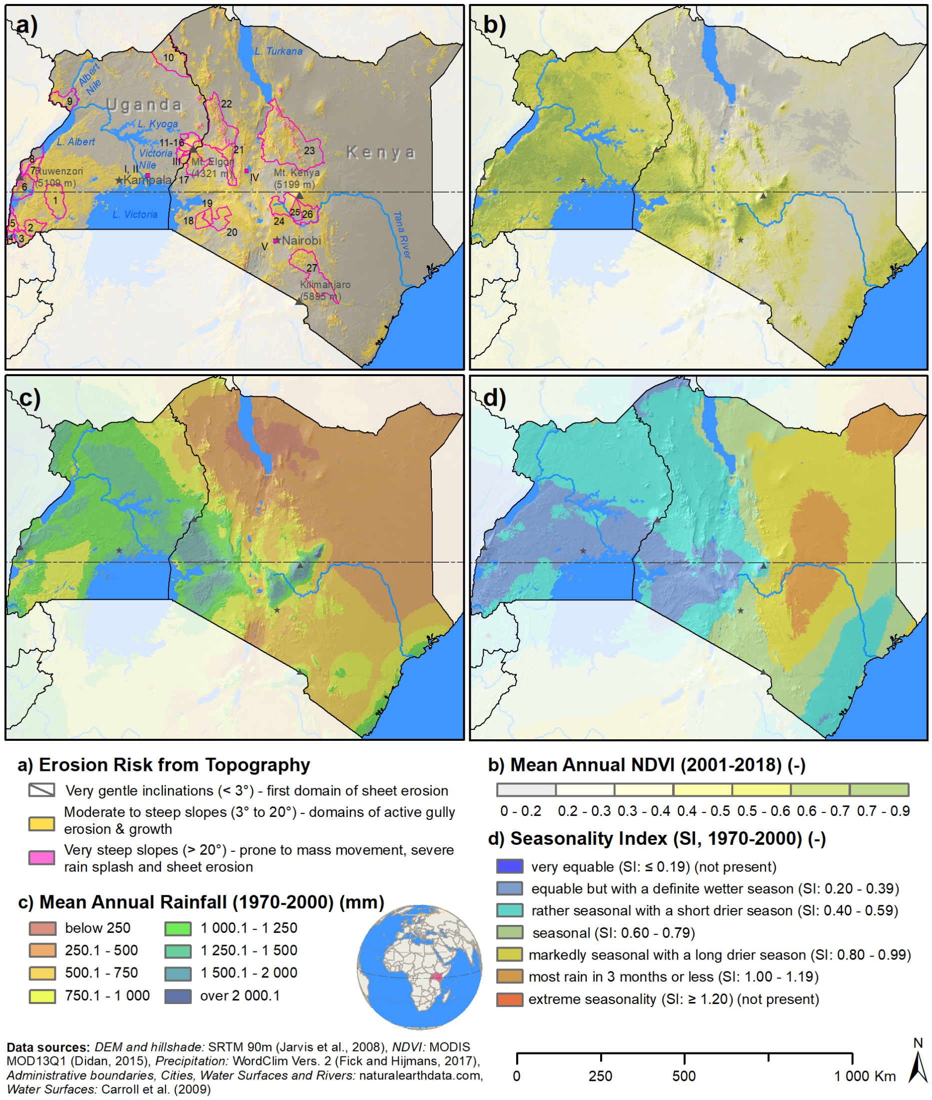

Figure 1. Study area ~~covering the countries~~ of Kenya and Uganda. A classification of the soil erosion risk after Ebisemiju (1988) (a), the mean annual MODIS NDVI as a proxy for vegetation cover (b), ~~and~~ mean annual rainfall (c), and the rainfall seasonality index (SI, Walsh and Lawler, 1981) (d) are plotted to characterize spatial properties of the study region. The boundaries for administrative units where the mean soil loss was assessed are shown with pink outlines in panel a). Locations of soil loss assessments from previous studies that were used for comparison are shown as pink squares. The hillshade is plotted in grey in the background to characterize the terrain topography.

("moderate risk") are evident in the South-West of Uganda and in a north-to-south band in Kenya, where the Western or Gregory Rift as part of the Great Rift Valley transects the country. The ~~area in~~ South-West of Uganda is characterized by a hilly topography with low elevation differences. In contrast, the erosion prone regions in Kenya are mostly characterized by larger elevation differences, e.g. escarpments. Very steep slopes that exhibit a high risk of erosion from topography are evident around mountain massifs, e.g. Ruwenzori (5109 m a.s.l., Uganda), Mt. Elgon (4321 m a.s.l., Uganda and Kenya) or Mt. Kenya (5199 m a.s.l., Kenya). Additionally, high erosion risk prone areas are evident in the south-western corner of Uganda and along the Rift Valley in the ~~northe rn~~ northern part of Kenya. Fig. 1b) shows the mean annual MODIS NDVI (Didan, 2015) for the period 2001 - 2018 as a proxy for the vegetation cover. Higher values in NDVI show pixels with high vegetation cover, where a lower risk of water erosion due to ground cover can be assumed, and vice-versa. Kenya exhibits a large variability in NDVI with low values in the arid to semi-arid northern and south-eastern parts. Higher vegetation cover is present at the coast towards the Indian Ocean, around Mt. Kenya, but also around Lake Victoria in the western part of the country. Uganda shows a rather homogeneous vegetation distribution, with some semi-arid areas in the north-east showing a lower vegetation cover.

Fig. 1c) shows the long-term mean annual rainfall (based on WorldClim Version2 for the period 1970 – 2000, Fick and Hijmans, 2017) as a proxy for the erosivity by rainfall. This assumes that larger annual rainfall values lead to higher erosion rates. Rainfall and vegetation cover are clearly connected. Hence, a more homogeneous rainfall pattern is visible for Uganda. Dryer areas in the south-west and north-east receive around 750 – 1000 $\mathrm{mm\ yr^{-1}}$ of precipitation. The center of the country is wetter with around 1000 – 1500 $\mathrm{mm\ yr^{-1}}$. In Kenya, wetter areas are evident around Lake Victoria and Mt. Kenya, receiving 1500 – 2000 $\mathrm{mm\ yr^{-1}}$ or even higher. The northern part of the country only receives 250 – 500 $\mathrm{mm\ yr^{-1}}$. Here, areas around Lake Turkana are very dry, with an annual precipitation of less than 250 $\mathrm{mm\ yr^{-1}}$. In accordance with vegetation cover, the coast is wetter (1000 – 1250 $\mathrm{mm\ yr^{-1}}$). Between the coast and the central highlands, a dry belt is visible (500 – 750 $\mathrm{mm\ yr^{-1}}$). To accompany the distribution of the mean annual rainfall, the seasonality of the rainfall (SI, Walsh and Lawler, 1981) is illustrated in Fig. 1d). The rainfall around the Lake Victoria is classified as as equable with a definite wetter season. The rainfall in the remaining parts of Uganda and along the coast of Kenya is rather seasonal with a short drier season. North and central Kenya are markedly seasonal with long dry seasons and only short wet periods.

3 Methods and Data Basis

3.1 The Universal Soil Loss Equation (USLE)

The general form of USLE-type equation is as follows:

$$A = R \times K \times LS \times C \times P \tag{1}$$

where A is the long-term average annual soil loss in $\mathrm{tons\ ha^{-1}\ yr^{-1}}$, R is the rainfall erosivity in $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$, K is the soil erodibility factor in $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$, L and S are the unitless slope length factor and the slope steepness factor (that are usually evaluated together as the topographic factor LS (Renard et al., 1997)), C is the unitless cover management factor, and P is the unitless support practice factor.

3.2 Estimation of USLE model inputs

To address the impact of different USLE input factor realizations on the simulation of the soil loss A, we generated a set of realizations for each of the four USLE input factors R, K, LS, and C. Methods to calculate the inputs were considered that were either used in previous large scale applications or that were specifically developed for Eastern Africa (or regions with similar climatic, topographic, and vegetation conditions). The implemented methods are described below. Further details to the input factor generation is provided in the supplementary materials section S.1. The support practice factor P was excluded from the analysis, as large scale data to derive estimates for P are very limited. Previous large scale studies, for example, inferred the P factor from relationships with the land use (e.g., Yang et al., 2003), ~~or~~ the land cover and slope (Fenta et al., 2020), implemented a global estimate of P for the entire study region (e.g., Karamage et al., 2017), or did not consider the P factor (e.g., Borrelli et al., 2017).

The rainfall erosivity factor R relates the intensity of rainfall events to the kinetic energy that is available to erode soil particles (Wischmeier and Smith, 1987; Panagos et al., 2015a). Rainfall intensity records are hardly available for large domains. Thus, large scale erosion studies often employ long-term monthly average or long-term annual average precipitation sums to infer R. We implemented long-term monthly precipitation provided by WorldClim Version2 (Fick and Hijmans, 2017) with a spatial resolution of 30 seconds~~and aggregated the monthly values to~~. The monthly precipitation sums were aggregated to a long-term annual precipitation. ~~We considered the following five~~ To account for the seasonality of the rainfall the monthly precipitation sums were employed to calculate the Modified Fournier Index (MFI, Arnoldus, 1980). In total, we considered six methods that relate long-term mean annual precipitation (P_{annual}) to R~~, but differ in their type of mathematical relationship~~ and one method that relates the MFI to R (Fig. 2a)).

Roose (1975) and Moore (1979) developed relationships between mean annual rainfall sums and R based on station data in Western and Eastern Africa, respectively. Karamage et al. (2017) used the method developed by Lo et al. (1985) to calculate R for Uganda. The method of Renard and Freimund (1994) was developed for USA precipitation station data and has been employed in global applications (e.g., Naipal et al., 2015; Yang et al., 2003). Nakil (2014) developed a relationship between precipitation and R for the highly variable rainfall patterns of the west coast of India. To assess and analyze the rainfall erosivity in Eastern Africa, Fenta et al. (2017) used two methods to infer R from long-term annual precipitation and from the MFI, respectively. Additionally, we considered recent products by Panagos et al. (2017) and Vrieling et al. (2014) that inferred R estimates from high temporal precipitation data. While Panagos et al. (2017) derived global estimates for R on a 1km grid based on a large global rainfall intensity data set to assemble the GloREDa data base, Vrieling et al. (2014) used the 3 hourly TRMM Multi-satellite Precipitation Analysis (TMPA) product (Huffman et al., 2007) to infer R estimates for the African continent in a 0.25° spatial resolution. In total we included seven realizations for R in this study (Fig. 2 a)).

The soil erodibility factor K describes the tendency of a soil to erode due to the erosive force of precipitation or surface runoff and can be related to soil physical and chemical properties (Panagos et al., 2014). Direct assessments of the soil erodibility are only available at a plot scale. Large scale erosion studies employ transfer functions that infer the soil erodibility from soil properties that are easier to acquire. Several global soil data products are available that provide physical and chemical soil properties with different spatial resolution. We implemented soil information from SoilGrids250m (Hengl et al., 2017) and the Global Soil Dataset for use in Earth System Models (GSDE, Shangguan et al., 2014). Layers of mass fractions of sand (Sa), silt (Si), and clay (Cl), the soil organic carbon content (orgC) and the fraction of coarse fragments (CRF) were acquired for the available soil depths and weighted average values for 0-10 cm were calculated. The aggregated soil layers were used in three transfer functions that were employed in previous large scale studies to compute K. We applied the method of Wischmeier and Smith (1987) and followed the procedure suggested by Panagos et al. (2014) and Borrelli et al. (2017) to compute K from the SoilGrids250m layers. The method of Wischmeier and Smith (1987) requires Sa, Si, Cl and organic matter content (OM) as inputs. Additionally, information on soil structure (s) and soil permeability (p) is relevant. Borrelli et al. (2017) derived these properties from soil classes according to the World Reference Base (WRB) and the USDA soil texture classification systems that are available for SoilGrids250m. GSDE does not provide soil class layers. Thus, the parameters s and p were kept constant when using the GSDE as input, following a procedure by Tamene and Le (2015). We further implemented the methods of Williams (1995) and Torri et al. (1997). Both methods require values of Sa, Si, Cl and OM as inputs. The soil products SoilGrids250m and GSDE in combination with three transfer functions resulted in six realizations of the K factor (Fig. 2b)).

The slope length and steepness factor LS represents the influence of the terrain topography on soil erosion (Panagos et al., 2015b). A digital elevation model (DEM) is the basis to derive the LS factor. In this study we implemented the SRTM v4.1 90m DEM (Jarvis et al., 2008) and the ASTER GDEM V2 (NASA/METI/AIST/Japan Spacesystems, and U.S./Japan ASTER Science Team, 2009) with a 30m resolution. ASTER GDEM V2 data was aggregated and projected to the 90m grid of SRTM v4.1 for comparability, but also because our computation capacities were insufficient to calculate soil erosion rates on a 30m grid for the study extent. Three methods were applied from Moore et al. (1991), Desmet and Govers (1996), and Böhner and Selige (2006) that are available from the System for Automated Geoscientific Analyses (SAGA) v. 2.1.4 (Conrad et al., 2015). Together with the two DEM products six realizations of the LS factor (Fig. 2c)) were computed. Intermediate steps such as the reprojection of the ASTER GDEM V2, DEM fill, the calculation of flow direction or flow accumulation were processed in ArcMap 10.6 (ESRI, 2012). In the calculation of LS using the method of Desmet and Govers (1996) we followed the steps described in Panagos et al. (2015b). The use of ASTER GDEM v2 introduced strong noise in the computed LS layers that results from artifacts in the remote sensing data. Particularly, the computed soil erosion in flat areas was strongly affected by the noise signal, rendering the ~~result unusable~~ results unusable (see section S.3 and Fig. S.1 in the supplementary document). Thus, we excluded the LS realizations using ASTER GDEM v2 in the analysis and only considered three out of the six generated realizations for the LS factor (Fig. 2 c)).

The cover management factor C subsumes the impacts of vegetation cover and land management on soil erosion (Wischmeier and Smith, 1987; Panagos et al., 2015c). For large scale studies we identified two main approaches to compute C (Fig. 2d)); i) to infer C from vegetation indices from satellite based remote sensing products (e.g., Karamage et al., 2017; Naipal et al., 2015; Tamene and Le, 2015; Van der Knijff et al., 2000) and ii) to join land cover classification products with agricultural statistics and C factor literature values to compile a continuous C factor layer (e.g., Borrelli et al., 2017; Panagos et al., 2015c; Bosco et al., 2015; Yang et al., 2003).

For the computation of C from NDVI vegetation indices we implemented the method of Van der Knijff et al. (2000), who proposed a non linear relationship between NDVI and C. We acquired 16 day MODIS NDVI averages (Didan, 2015) from 2000 to 2012 and aggregated them to a mean NDVI layer. We calculated the annual mean NDVI (see e.g., Van der Knijff et al., 2000; Tamene and Le, 2015) and the mean NDVI averages over the two rainy seasons March to May and October to November as proposed by Karamage et al. (2017). Both long-term mean NDVI layers were used to compute C factor realizations with the equation of Van der Knijff et al. (2000).

Two land cover products, the MODIS Collection 5 LC with a spatial resolution of 250m (Channan et al., 2014; Friedl et al., 2010) and the ESA CCI LC Map v2.0.7 with a spatial resolution of 300m (ESA, 2017) served as base ~~layers for the join with agriculturalstatistics and C~~ land cover layers. The agricultural, forest, and naturally vegetated land cover in these maps were superimposed with C factor literature values. The C factor values for agricultural land uses were calculated based on agricultural statistics. Two agricultural statistics were used that provide information on crop areas at different spatial scales. i) National agricultural surveys for Kenya on ward level (KNBS, 2015) and for Uganda on county level (UBOS, 2010) were harmonized. ii) Monfreda et al. (2008) provides global gridded crop shares of 175 crops with a spatial resolution of 5 minutes. We assigned C factor literature values from Panagos et al. (2015c) and Angima et al. (2003) to all crops found in the national agricultural surveys and the grid layers from Monfreda et al. (2008). Based on the crop shares in the administrative units of Kenya and Uganda and for the crop shares in each grid cell of Monfreda et al. (2008) we calculated weighted average C values as proposed in Panagos et al. (2015c). C values for non agricultural land uses of the MODIS LC were estimated according to Panagos et al. (2015c) varying the C values for forest between boundaries based on the MODIS vegetation continuous fields (VCF) tree cover product. ESA CCI LC classifies the land cover as shares between different land uses (e.g. Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)). In this case, C values were estimated by calculating weighted averages between the calculated average C values for agricultural areas and literature values (Panagos et al., 2015c) for non agricultural land uses according to the given fractions of the land cover classes. The combination of the two land cover products and the two agricultural statistic products resulted in four realizations for the C factor.

3.3 Estimation of soil loss

In total ~~7~~9, 6, 6 (3), and 6 realizations were generated for the USLE input factors R, K, LS, and C, respectively. The combination of all input factors to assemble USLE model setups ~~resulted in 1512~~ would have resulted in 1944 realizations of the USLE model. The LS factor realizations that were generated with the ASTER GDEM V2 were however excluded from the model ensemble, as they showed large noise ratios~~and the~~. The number of analyzed USLE model setups was therefore halved to ~~756.~~ 972. For the overlay of the generated USLE input layers, all layers were reprojected to the grid of the SRTM v4.1 90m DEM and the long-term mean annual soil loss A was calculated for all model combinations in the study region of Kenya and Uganda using Eq. 1.

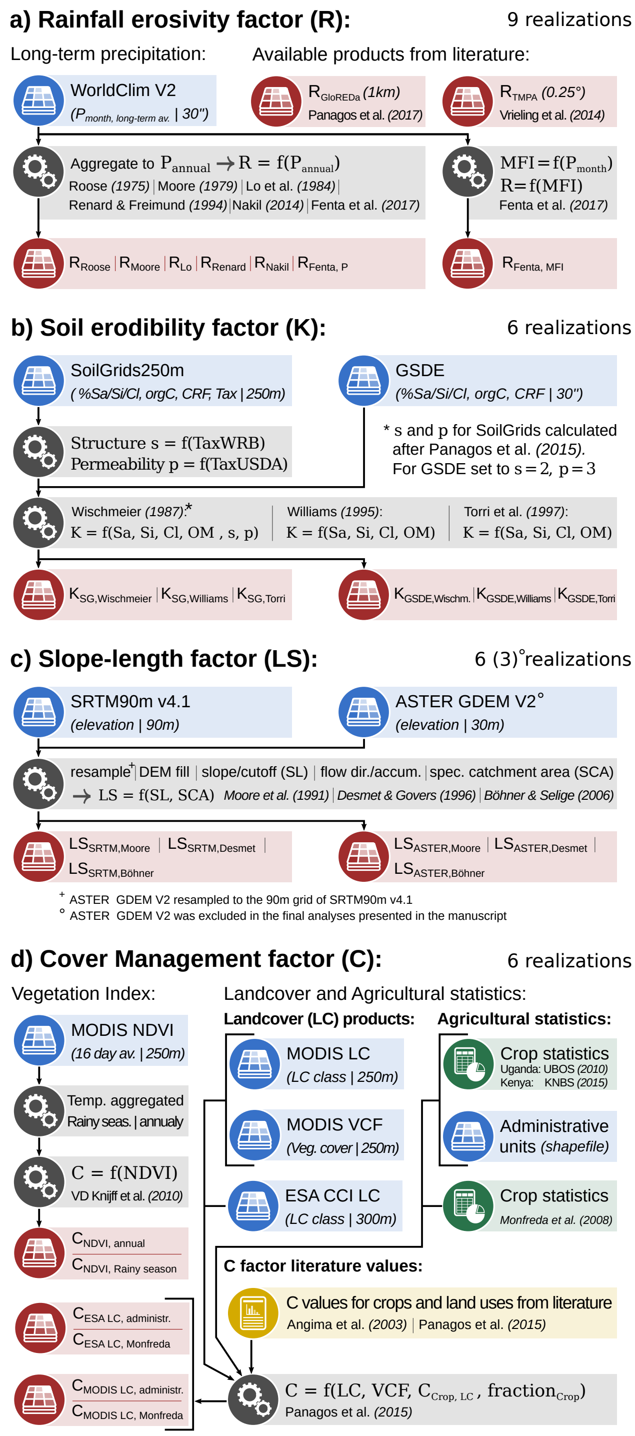

Figure 2. Methodological framework to generate the realizations of the USLE model input factors R, K, LS, and C.

3.4 Analysis of spatially distributed soil loss estimates

The ensemble of ~~756~~ 972 spatially distributed soil loss estimates with spatial resolution of 90 m were summarized in each grid cell employing descriptive statistical measures. In each grid cell we calculated mean and median values to estimate an average soil loss from the USLE model ensemble. The range of the minimum and maximum soil loss A in a grid cell indicates the variation of the ensemble simulations in a grid cell (i.e. the disagreement between the model setups).

A common concept in the erosion literature is to relate soil loss to soil formation rates and therefore classify the soil loss as sustainable (tolerable) or non-sustainable (e.g., Blanco-Canqui and Lal, 2008; Montgomery, 2007; Van-Camp et al., 2004), or to group soil loss based on the severity of soil removal (e.g., Zachar, 1982; FAO-PNUMA-UNESCO, 1980). ~~Suggested~~ Literature values for tolerable levels of soil loss ~~(T)~~ vary between 5 and 12 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ on a global scale (Montgomery, 2007; Blanco-Canqui and Lal, 2008; Zachar, 1982). Karamage et al. (2017), Bamutaze (2015), Morgan (2009), or Lufafa et al. (2003) used 10 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ as ~~threshold value T~~ a threshold value to classify tolerable soil loss for studies conducted in Eastern Africa. In this study low soil losses were classified by employing the same threshold. Yet, no information on soil formation was included and thus the term *tolerable* is misleading. Consequently a soil loss between 0 and 10 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ is defined as *slight* soil loss, as suggested by Fenta et al. (2020).

For soil loss levels larger than ~~T~~ 10 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ we implemented the soil ~~loss~~ removal classification after FAO-PNUMA-UNESCO (1980, implemented e.g. in Hernando and Romana (2015) or Olivares et al. (2016)) where a soil loss between 10 and 50 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ is considered to be moderate, a soil loss between 50 and 200 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ to be high, and a soil loss larger than 200 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ to be severe. In each grid cell we classified the simulated soil losses from the ~~756~~ 972 USLE model setups into the four defined soil loss classes and calculated the frequencies for each soil loss class as follows:

$$f_{i,m,n} = \begin{cases} 0 & \text{if } A_{i,m,n} \notin [A_{class,lower}; A_{class,upper}) \\ 1 & \text{if } A_{i,m,n} \in [A_{class,lower}; A_{class,upper}) \end{cases} \tag{2}$$

$$f_{m,n} = \frac{\sum\limits_{i=1}^{N} f_{i,m,n}}{N} \tag{3}$$

where $f_{m,n}$ is the frequency of models that calculated a soil loss between the defined boundaries $A_{class,lower}$ and $A_{class,upper}$ of the respective class in the grid cell (m,n) and based on the ~~$N = 756$~~ $N = 972$ USLE model setups. A step function assigns the probabilities $p_{i,m,n} = 1$ or $p_{i,m,n} = 0$ to a model i if the soil loss $A_{i,m,n}$ that was calculated with the model i for the grid cell (m,n) is included or excluded from a class interval.

3.5 Analysis of the USLE input factors

In the case of a simple model, such as the USLE, uncertainties in the inputs can be analytically propagated through the model to infer the uncertainties in the outputs (Beven and Brazier, 2011). Thus, the sensitivity of the calculated soil loss for the ranges of the input factors can be analyzed analytically. We assessed the importance of the USLE input factors on the simulation of the soil loss in each grid cell by calculating the fraction between the range in soil loss that is caused by an input factor I_j and the total range of A that results from the entire model ensemble in that grid cell:

$$s_{j,m,n} = \frac{(\max(I_{j,m,n}) - \min(I_{j,m,n})) \cdot \prod_{k \neq j} \max(I_{k,m,n})}{\left(\prod_{k} \max(I_{k,m,n}) - \prod_{k} \min(I_{k,m,n})\right)} \tag{4}$$

where $s_{j,m,n}$ is the sensitivity of the input factor I_j in the grid cell (m,n), I is the set of the analyzed input factors R, K, LS, and C, and k is the index of the respective input factor. The resulting sensitivity measure is normalized between 0 and 1, where a sensitivity $s_{j,m,n} = 1$ means that the total range of the calculated soil loss can result from varying the input I_j and 0 means that this input shows no variation between its realizations in the grid cell (m,n). In each grid cell the input factors are ranked based on their sensitivities and visualized to get a spatial reference of the importance of the model inputs.

3.6 ~~Analysis of soil~~ Soil loss ~~on~~ assessment at administrative ~~level~~levels and comparison to other studies in Uganda and Kenya

We assessed the soil loss on a national level for Kenya and Uganda as well as on an administrative levels for 27 administrative units in Uganda and Kenya. An aggregation of the calculated soil losses to clearly defined spatial units allowed a comparison of the USLE model ensemble results to previous erosion studies in Kenya and Uganda that employed single USLE model setups and evaluated the soil losses for these spatial domains. On a national level we compared the USLE model ensemble results to the results presented in Fenta et al. (2020). For the comparison we employed the descriptive statistical measures that were computed spatially distributed for the study area in section 3.4. The spatially distributed soil loss quantiles were aggregated in two different ways. First, mean values for Uganda and Kenya were computed for the spatially distributed median, minimum, and maximum soil losses and compared to the mean soil losses in Fenta et al. (2020). Second, the quantile soil losses were grouped into soil loss levels based on a classification used in Fenta et al. (2020) and area proportions were calculated for each soil loss level. These area proportions were compared to the area proportions of the soil loss levels reported in Fenta et al. (2020).

For all administrative units and all USLE model setups the mean soil loss was calculated. The distribution of the mean soil loss in each administrative ~~units~~ unit was analyzed with descriptive statistics. Employing Eq. (3) soil loss levels were determined for all grid cells in the respective administrative units and for all USLE model setups. The areas of each soil loss class calculated from all USLE model setups per administrative unit were summed up to compute the average share of a soil loss class for each administrative unit. Only administrative units located in the erosion prone regions that are indicated in Fig. 1 are analyzed in the main document ~~below. A~~ and compared to the soil losses on the administrative level presented in Karamage et al. (2017). To provide a complete summary of the ~~results~~ soil losses on the administrative level for all counties of Kenya and districts of Uganda ~~can be found in~~ we refer to the supplementary document ~~in section S~~section S.5 and the figures S.2 and S.3.

3.7 Comparison of the soil loss estimates to in field assessments

To provide a reference for the USLE ensemble simulations we used literature values of long-term mean annual soil loss from in-field assessments. García-Ruiz et al. (2015) compiled a comprehensive literature review for global soil loss rates, where three sources provided values for five sites within the study area of Kenya and Uganda. All three sources, however, applied different methods to assess the soil loss and cover a wide range of spatial domains. Sutherland and Bryan (1990) estimated the soil loss from the 0.3 km^2 Katiorin catchment located in the Lake Baringo drainage area in Kenya based on an in-stream discharge and suspended sediment sampling. Sutherland and Bryan (1990) estimated an average soil loss for the Katiorin catchment of 73 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ with a range between 16 and 96 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$. Kithiia (1997) reported results from soil loss monitorings in tributaries of the Athi River Basin conducted by the Kenian Ministry of Water Development. From the tributary sampling sites in the Athi River Basin we selected the 41 km^2 Riara catchment with an average reported sediment load of $1474\ \mathrm{tons\ yr^{-1}}$ (0.36 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$). Bamutaze (2010) preformed an erosion plot experiment in the Sinje catchment at Mt. Elgon in Uganda. Based on a two year monitoring, Bamutaze (2010) estimated a mean soil loss of 0.838 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ with a range between 0.185 and $1.761\ \mathrm{tons\ ha^{-1}\ yr^{-1}}$. De Meyer et al. (2011) assessed the soil loss from 36 farm compounds in the two villages Iguluibi and Waibale close to the northern shore of Lake Victoria in Uganda. De Meyer et al. (2011) assessed the soil loss by reconstructing the historic surface level and calculating the lost soil volume. The estimations range between 56 and 460 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ in Iguluibi and 27 and 135 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ in Waibale.

To compare the ensemble soil loss estimations in this study with the literature values we calculated mean soil losses for grid cells that cover the original study site locations. Statistical measures were aggregated for the calculated site averages and plotted against the measured soil losses acquired from the selected studies.

3.8 Used software

The entire calculation of the USLE model realizations, most part of the input factor generation and the entire analysis of the simulation results was performed in the R programming environment (R Core Team, 2019). Spatial tasks and analyses were performed using the spatial R packages `raster` (Hijmans, 2019), `sf` (Pebesma, 2018), `rgdal` (Bivand et al., 2019), and `fasterize` (Ross, 2018). Data handling with SQLite data bases was managed through interfacing with the `RSQLite` (Müller et al., 2018) and `dbplyr` (Wickham and Ruiz, 2019) packages. Data analyses employed the R packages `dplyr` (Wickham et al., 2019b), `forcats` (Wickham, 2019), `lubridate` (Grolemund and Wickham, 2011), `purrr` (Henry and Wickham, 2019), `tibble` (Müller and Wickham, 2019), and `tidyr` (Wickham and Henry, 2019). Parallel computing to run some analyses was performed with the R packages `foreach` (Microsoft Corporation and Weston, 2017b), `doSNOW` (Microsoft Corporation and Weston, 2017a), and `parallel` (R Core Team, 2019). LS factor realizations were generated with the LS Module in SAGA GIS (Conrad et al., 2015). Spatial maps were prepared in ArcGIS (ESRI, 2012) and in the R environment `ggplot2` (Wickham et al., 2019a) was used for all other figures.

4 Results

4.1 Analysis of the soil loss simulated with the USLE model ensemble

Overall, the calculated soil losses by our models follow the spatial pattern indicated by the potential erosion risk from topography that was presented in Fig. 1a). Both, the ensemble mean (Fig. 3a)) and the median soil loss (Fig. 3b)) show increased soil losses where moderate or high erosion risks were identified based on the slope thresholds suggested by Ebisemiju (1988). Although the soil loss levels shown in Fig. 3 differ from the soil loss levels that were used by Fenta et al. (2020), the spatial patterns of soil loss by water reported in Fenta et al. (2020) strongly agree with the patterns of the mean and median soil losses shown in Fig. 3a) and b). Mean soil losses of larger than 50 tons ha^{-1} yr^{-1} were found in the south-western corner of Uganda around Lake Bunyoni and along the Rift Valley in the North-West of Kenya. ~~Particularly, excessive~~ Excessive soil losses that exceed 200 tons ha^{-1} yr^{-1} were calculated for the steep slopes around the Ruwenzori Mountains, Mt. Elgon, and Mt. Kenya with ensemble mean soil losses of up to 1865, 1663, and 1438 tons ha^{-1} yr^{-1}, respectively. Large variations in the calculated soil losses in each grid cell in combination with highly positively skewed distributions are two reasons why the calculated mean soil losses are generally larger than the median values.

The strong discrepancy between the USLE model setups is evident from the comparison of the minimum calculated soil losses (Fig. 3c)) and the maximum soil losses (Fig. 3d)) in each grid cell. While combinations of USLE model input factors were present in the model ensemble that calculated soil losses below 10 tons ha^{-1} yr^{-1} for 99 % of the study region and soil losses below 100 tons ha^{-1} yr^{-1} for the entire study region, other input factor combinations resulted in soil losses above 200 tons ha^{-1} yr^{-1} for over 45 % of the study region and substantial soil losses of at least 50 tons ha^{-1} yr^{-1} for over 85 % of the study region.

Fig. 4 provides a different perspective of the same ensemble simulations. Each grid cell shows the frequency for the defined soil loss levels *~~tolerable~~slight*, *moderate*, *high*, and *severe* (panels a)-d) respectively) that were predicted by the model members of the ~~ULSE~~ USLE model ensemble. For large areas in the Northern Region of Uganda, the south of the lakes Kyoga and Albert in Uganda, and the Northeast Province and the northern parts of the Eastern Province in Kenya over 90 % (and in many cases all) of the USLE model setups calculated ~~tolerable~~ slight soil losses. In the topographically heterogeneous regions of the Uganda Plateau, the South West of Uganda and the Gregory Rift in Kenya, a substantial share of up to 40 % of all model setups calculated a ~~tolerable~~ slight soil and the majority of model setups resulted in moderate soil losses. Only along the steep mountain ridges in the Rift Valley and the mountain massifs of Mt. Kenya, Mt. Elgon, the Ruwenzori Mountains and the region around Lake Bunyoni a substantial part of USLE model setups calculated high and severe soil losses (yellow and local red regions in Fig 4 c) and d)).

Fig. 5 combines the soil loss classification and the (un)certainties in the prediction of soil loss levels based on the USLE model ensemble into one representation. The dominant soil loss levels that a majority of model setups predicted for a grid cell are shown in green (*~~tolerable~~slight*), blue (*moderate*), orange (*high*), and purple (*severe*). The lightness of the colors indicates the percentage of models that calculated a soil loss within the respective soil loss classes. To highlight the complex patterns

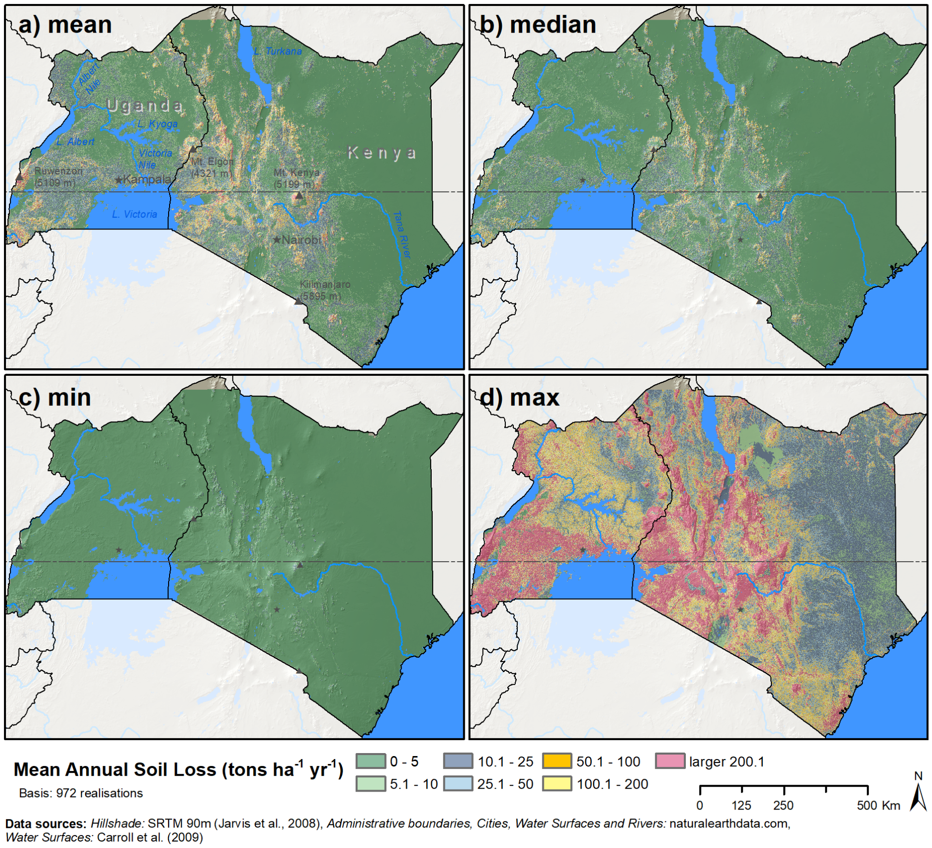

Figure 3. Descriptive statistics calculated for each grid cell based on the ~~756~~ 972 USLE model realizations. Panels a) to d) show the mean, median, minimum, and maximum long-term annual soil erosion in each grid cell.

that result from the ensemble soil loss estimations in topographically heterogeneous regions, we show the Mt. Elgon (Fig. 5 b)), Lake Bunyoni (Fig. 5 c)), and Mt. Kenya (Fig. 5 d)) regions in detail.

The strong agreement between the USLE model setups to calculate ~~tolerable~~ slight soil loss for the generally flat regions of Kenya and Uganda (shown in purple in Fig. 4 a)) is visible in dark green in Fig. 5 a). The soil loss level patterns in the erosion prone areas of Mt. Elgon, Lake Bunyoni, and Mt. Kenya clearly follow the topographic patterns of these regions, with high and severe soil loss levels along the mountain ridges and ~~tolerable~~ slight to moderate soil losses in the valley bottoms. The agreement of the USLE model setups to predict the same soil loss level in such heterogeneous topographies is generally lower, showing percentages of 25 to 75 %. Only along the very steep slopes of the mountain massifs (and particularly at the top of Mt. Kenya with its steep slopes and low vegetation cover) a large majority of the USLE model ensemble predicted a severe soil loss (center of Fig. 5 d)). Although the entire Mt. Elgon and the Mt. Kenya massifs show moderate to steep slopes (see. Fig. 1 b)), a large majority of the USLE model ensemble (>75 %) calculated ~~tolerable~~ slight soil losses for the densely forested northern part of Mt. Elgon and the forest belt around Mt. Kenya.

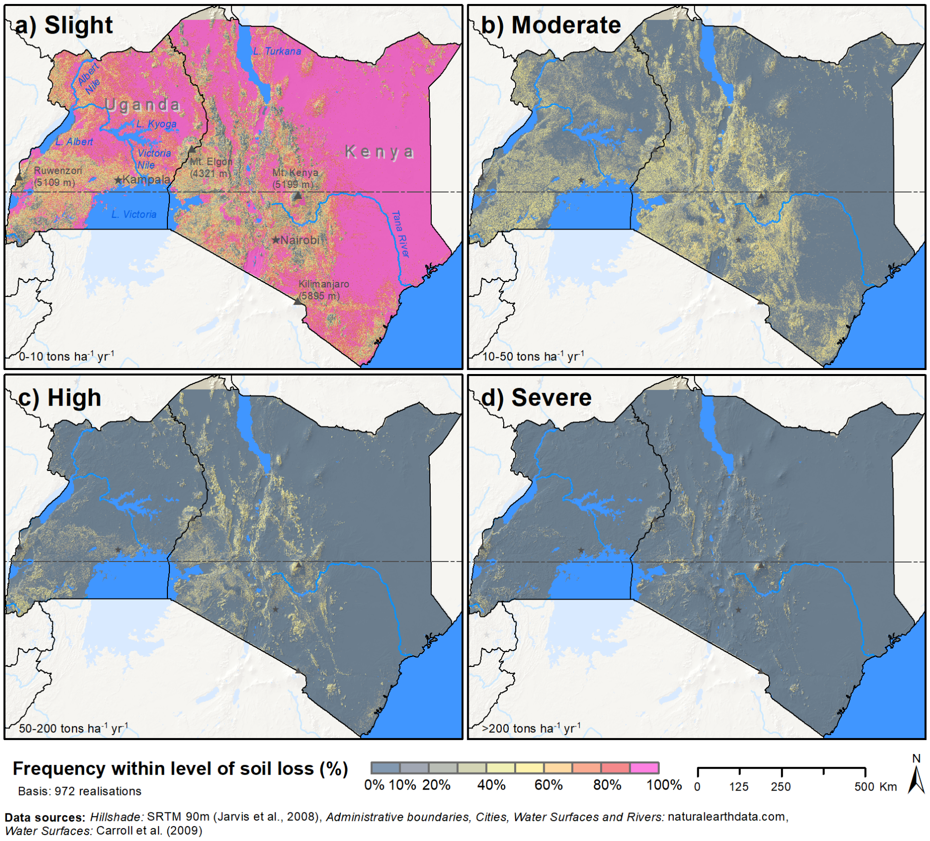

Figure 4. Frequency of USLE model ensemble members to predict one of the four soil loss classes ~~*tolerable*~~ *slight* (0 – 10 tons ha^{-1} yr^{-1}) (a), *moderate* (10 – 50 tons ha^{-1} yr^{-1}) (b), *high* (50 – 200 tons ha^{-1} yr^{-1}) (c), and *severe* (>200 tons ha^{-1} yr^{-1}) (d), based on the soil loss classification after FAO-PNUMA-UNESCO (1980). The pixel color illustrates the percentage of models from the model ensemble that calculated a soil loss in between the respective class boundaries.

4.2 Analysis of the USLE input factors

To analyze and compare the individual realizations for the USLE inputs summary statistics were calculated for all grid cells of the study area. A detailed summary for all inputs is presented in the supplementary document section S.2. The median values of the R factor realizations range between 1581 and 6851 $\text{MJ mm ha}^{-1}\ \text{h}^{-1}\ \text{yr}^{-1}$ where the method of Nakil (2014) shows the lowest value and the method of Roose (1975) the largest median value. All other methods show comparable median values with a range of 2243 – 3652 $\text{MJ mm ha}^{-1}\ \text{h}^{-1}\ \text{yr}^{-1}$. The maximum R values show, however, a wide range between the implemented methods, where R_{Nakil} again shows the lowest value (6875 $\text{MJ mm ha}^{-1}\ \text{h}^{-1}\ \text{yr}^{-1}$) and R_{TMPA} a 4.5 times larger value with 31068 $\text{MJ mm ha}^{-1}\ \text{h}^{-1}\ \text{yr}^{-1}$. The maximum values are however very local and the values of the third quantile of most of the R values for the different methods are within a narrow range of 3606 – 5463 $\text{MJ mm ha}^{-1}\ \text{h}^{-1}$ yr^{-1}. Summarized for the entire study area the implemented methods do not show any clear differences between the different

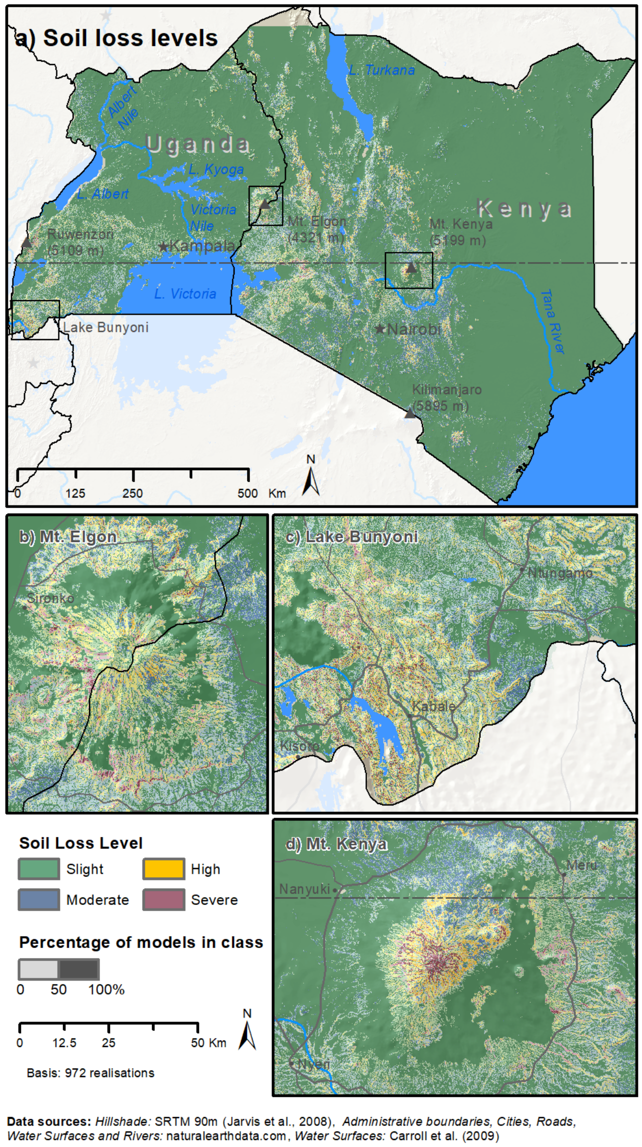

Figure 5. Dominant soil loss levels. The color shows the soil loss level predicted by the majority of USLE model setups. The lightness of the color indicates the percentage of models that predicted the dominant soil loss level. Panel a) shows the study area of Kenya and Uganda. The panels b), c), and d) show erosion prone areas around Mt. Elgon, Lake Bunyoni, and Mt. Kenya, respectively.

types of methods that were implemented. The quantile R values for $R_{GloREDa}$ (from high temporal resolution precipitation data) for example, greatly compare to the quantiles of $R_{Fenta,MFI}$ that considers the rainfall seasonality, or the method of Moore (1979), which is based on long-term annual rainfall.

For the K factor realizations in contrast a clear difference can be observed between the implemented methods. While the K factor realizations that employed the methods of Wischmeier and Smith (1987) (as implemented in Panagos et al. (2015c)) and Williams (1995) resulted in comparable values, with 0.005 – 0.038 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ and 0.011 – 0.039 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ respectively, when applied to the SoilGrids250m data set, the method of Torri results in a substantially larger range (0.00 – 0.109 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$). Overall, all quantiles for the K values that employ the method of Torri are approximately 4 times larger than the respective quantiles for the other two methods.

Similar findings are visible for the realizations for the LS factor. The median, the first and the third qunatiles for the method of Desmet and Govers (1996) resulted in substantially larger LS values compared to the methods of Böhner and Selige (2006) and Moore et al. (1991) with median values of 0.334, 0.074, and 0.013, respectively, when implemented with the SRTM v4.1 90m DEM. The methods of Böhner and Selige (2006) and Moore et al. (1991) resulted, however, in substantially larger maximum values (70.63 and 91.48) compared to the method of Desmet and Govers (1996) (19.31).

Overall, the summary statistics for the C factor values show clear differences between the methods that employed the MODIS NDVI, the ESA CCI LC, and the MODIS LC, whereas the impact of the implemented agricultural statistics, or the temporal aggregation of the NDVI on the summary statistics of the C factor is low. The median (0.214 and 0.175), the third quantile (0.402 and 0.355) and the maximum value (1) of the C factor realizations that employed the NDVI are approximately twice as large as the respective quantiles for the methods that implemented the ESA CCI LC ($median$ = 0.080, q_{75} = 0.15 and 0.232, $maximum$ = 0.5), and the MODIS LC ($median$ = 0.15, q_{75} = 0.15 and 0.232, $maximum$ = 0.5) land cover products. The first quantiles of the C factor realizations that employed the NDVI (0.059 and 0.472) show however 2 and 3 times smaller values than the first quantiles for the realizations that implemented the ESA CCI LC (0.080) and the realizations that implemented MODIS LC (0.150), respectively.

The range of the calculated soil loss A in a grid cell is the direct result of the different values stemming from the various input factor realizations. A large range in the values of an input factor in a grid cell has a greater impact on the resulting uncertainties of the calculated soil loss compared to input factors where the different realizations show similar values. The analysis of the strongest impact of input factors on the uncertainties of A revealed clear spatial patterns at different spatial scales (Fig. ~~8~~ 6 a)). Over the whole domain, the input factors C, K, and LS were identified as the most important inputs for the uncertainties in soil loss in ~~34.74%, 31.39~~33.89%, 31.35%, and ~~28.55~~28.45% of the total study area, respectively. The R factor was only locally identified as the most relevant input factor in ~~5.32~~ 6.31 % of the total study area. The C factor and the K factors show large aggregated patterns in both countries. The importance of the LS factor, however, generally shows small structured, heterogeneous patterns scattered over the entire study region. Exceptions are visible in larger depressions along the Gregory Rift in zones where the slope is close to 0. Lake Magadi (100 km^2), an alkine lake located in an endorheic basin in the Rift Valley south of Nairobi, or a larger region in the east of Lake Turkana are the most distinct examples for large patterns of LS. Clusters of high importance of the R factor were only identified in high altitudes with generally large precipitation sums, but also in very dry regions in the northern Kenya, where the precipitation sums are close to 0.

Fig. ~~8~~ 6 b)-d) provides more detail of the spatial patterns of the input factors and their importance for the calculation of the soil loss in regions around Mt. Elgon, Lake Bunyoni, and Mt. Kenya (that were also analyzed in Fig 5). In contrast to Fig. ~~8~~ 6 a), finer-scale characteristics of input factor importance become visible. The patterns around the two mountains Mt. Elgon and Mt. Kenya show similarities. Although the R factor is spatially highly concentrated at the top of Mt. Kenya and only slightly

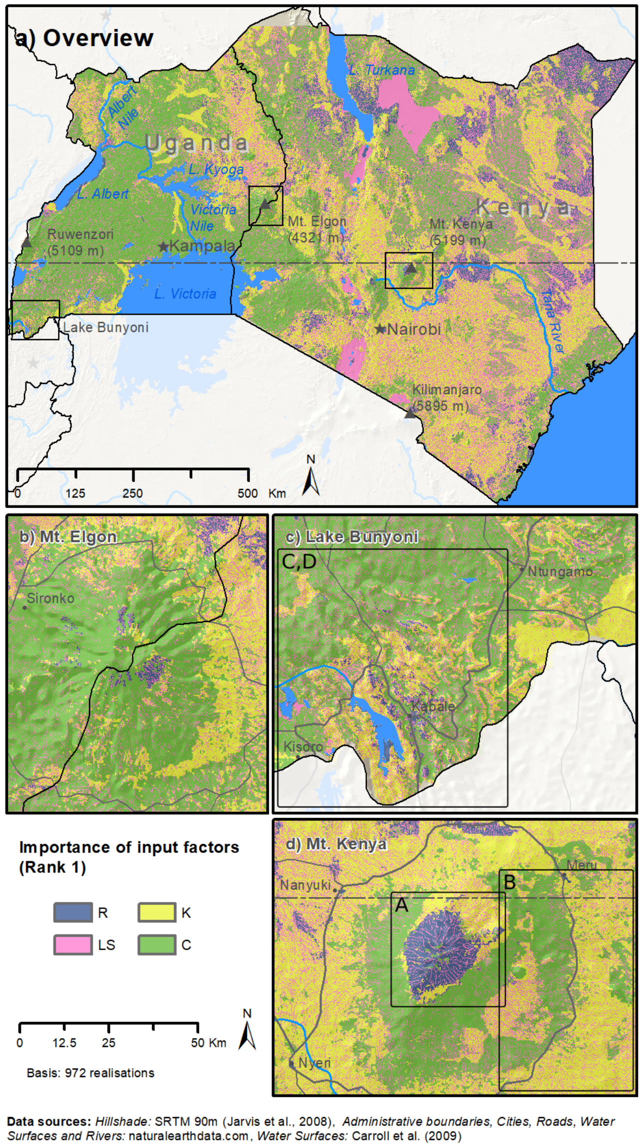

Figure 6. Most important USLE model input factors for the calculation of the soil loss A. The colours blue, yellow, pink, and green indicate whether the input factors R, K, LS, or C caused the largest range in the calculation of A in a grid cell. Panel a) shows the study area of Kenya and Uganda. The panels b), c), and d) show critical erosion hot spots around Mt. Elgon, Lake Bunyoni, and Mt. Kenya, respectively. The insets A) to D) indicate the extents for which the input factor realizations for R, K, LS, and C were analyzed in Fig. ~~9~~7.

visible on the east of Mt. Elgon, both regions show a high importance of the R factor for the calculation of A in high altitudes. High altitude areas are mostly characterised by a sparse observation network for precipitation. R is highly correlated to some, in our case spatially distributed, rainfall estimates. High uncertainties in rainfall records, but also in the modelling chain to derive remotely sensed precipitation explain these patterns. Moving down from the summits, belts of a high importance of the

C and K factor are visible. These distinct patterns result from the vertical bands of changes in vegetation in such mountainous regions and the impact of sparse and dense natural vegetation and agricultural land uses on the calculation of the C factor. The Lake Bunyoni region shows more heterogeneous patterns for the most important input factors. In the north, the calculation of A is affected by the C factor in large regions and the LS factor on very small scaled patterns. In the east and west of Lake Bunyoni, patterns for all input factors are visible that follow the terrain topography. The LS and K factor are the most relevant input factors for the calculation of A along the ridge lines, while the C factor becomes more important closer to the valley bottoms.

The importance of an input factor for the calculation of A in Fig. 6 results from the differences in the estimated input factor values for the individual input factor realizations. In ~~Fig. 9~~ addition to the general analysis on the quantiles of the input factor realizations for the entire study region, we analyzed the input factor realizations of R, K, LS, and K in the four regions A) to D) (indicated in Fig. ~~8)~~ 6) with greater detail in Fig. 7. For the analysis only grid cells in the defined extents A) to D) were selected ~~, which had the condition~~ and only (i) ~~that~~ where the respective input factor was the most relevant one and (ii) where the calculated soil loss was ~~calculated~~ classified to be high ~~to~~ or severe.

Case A) (Fig. ~~9~~ 7 A)) shows the differences of R factor realizations at the top of Mt. Kenya. ~~Generally~~In this specific case (and other locations with high altitudes, data not shown), a difference between the rainfall erosivity products derived from temporally high resolution rainfall (GloREDa (Panagos et al., 2017) and TMPA (Vrieling et al., 2014)) and the distributions of the R values obtained from long-term annual precipitation is visible. While both, GloREDa and TMPA show low R values between 1869 and 3486 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ and 3000 and 4602 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$, respectively, the methods of Roose (1975), Moore (1979), Renard and Freimund (1994), ~~and Lo et al. (1985)~~Lo et al. (1985), and Fenta et al. (2017) (employing P_{annual}) resulted in a wide range of R values between ~~4940~~ 4821 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ (minimum value using the method of ~~Lo et al. (1985)~~Fenta et al. (2017)) and 16207 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ (maximum value using the method of Roose (1975)). Hence, a strong impact of the selected equation to calculate R from long-term annual precipitation is observable. Only the ~~method of Nakil (2014)~~ methods of Nakil (2014) and the method of Fenta et al. (2017) (that employs the MFI) showed low R values in ~~the same~~ a comparable range as GloREDa and TMPA, with ~~a range between~~ ranges of 2590 ~~and~~ – 3757 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ and 3828 – 5046 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$, respectively. The method of Nakil (2014), however, ~~generally generated~~ resulted in very low R values overall (also where GloREDa and TMPA showed significantly larger R values), as outlined in the analysis of the entire study area (see also section S.2 in the supplementary document).

Case B) (Fig. ~~9~~ 7 B)) compares the K factor realizations in the south-eastern belt around Mt. Kenya. The six realizations of K show ~~a clear pattern that is strongly affected by the~~ the same pattern as it is observable for the entire study area. The methods that were employed to calculate K strongly affect the calculation of K, while the differences between the two soil products that were used are rather insignificant. ~~The~~ In this specific case in Fig. 7 B), the method of Torri et al. (1997) resulted in by far the largest K values between 0.069 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ and 0.088 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$. On average these values are three times larger than the ones calculated with the method of Williams (1995) (with a range between 0.021 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ and 0.031 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$) and up to 13 times larger than the values calculated with the method of Wischmeier and Smith (1987) when using the SoilGrids data set (with a range between 0.011 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ and 0.028 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$).

Case C) (Fig. ~~9~~ 7 C)) shows the differences between the the LS factor realizations along the ridges of the hills around Lake Bunyoni. Eventually, only the SRTM 90m DEM was used as input data ~~. Thus, Fig. 9~~ and is shown in Fig. 7. Panel C) compares the three methods of Moore et al. (1991), Desmet and Govers (1996), and Böhner and Selige (2006). While the methods of Moore et al. (1991) and Böhner and Selige (2006) resulted in comparable values with ranges between 1.47 and 3.90 and between 1.65 and 5.03, respectively, the method of Desmet and Govers (1996) resulted in five times larger values with a range between 8.22 and 18.79. In this specific case the method of Desmet and Govers (1996) resulted in values close to the overall maximum value that was calculated for the study region (19.31). The methods of Moore et al. (1991) and Böhner and Selige (2006) resulted in lower values although their maxima for the entire study region exceed the maximum value that results from the method of Desmet and Govers (1996) by a factor of 3 – 4.

Case D) (Fig. ~~9~~ 7 D)) compares the implemented C factor realizations for the same extent around Lake Bunyoni as ~~it was used in~~ for case C). In general two patterns are observable. A strong difference between the realizations that employ the NDVI as input and the C factor realization that were derived from land cover products and literature C factor values is visible. Further, using the gridded crop distribution product of Monfreda et al. (2008) to derive spatially distributed mean C factor values from the literature resulted in larger values compared to the implementation of agricultural census data on the administrative unit level for Kenya and Uganda. The impact of the used land cover product (ESA LC or MODIS LC) are low. Both realizations based on NDVI (NDVI, annual and NDVI, rainy season) show mean C factor values of 0.04 and 0.03, respectively. The C values for the realizations that employed crop data from Monfreda et al. (2008) and agricultural census data were on average six times and 4.5 times larger with mean values of 0.21 and 0.15 respectively. The results for this specific case contrast the general analysis of the C factor values for the entire study region, where C factor values of the realizations that implemented the NDVI are substantially larger compared to the methods that employed land cover products.

4.3 Soil loss assessment at ~~the~~ administrative ~~level~~levels and comparison to other studies

On a national level the results reported in Fenta et al. (2020) allow a comparison to ensemble soil loss estimates of this study. Fenta et al. (2020) calculated mean soil losses of 7.3 and 6.7 tons ha^{-1} yr^{-1} for Uganda and Kenya, respectively. While the USLE ensemble median soil losses show comparable values of 7.7 and 7.3 tons ha^{-1} yr^{-1} on average for Uganda and Kenya, the minimum and maximum average soil losses for the two countries that result from the USLE model ensemble show extreme ranges (Uganda: 0.3 – 301.2 tons ha^{-1} yr^{-1}, Kenya: 0.5 – 207 tons ha^{-1} yr^{-1}). Fig. 8 compares the area proportions for Uganda and Kenya that were shown in Fenta et al. (2020) to the summarized results from the USLE model ensemble. For a comparison the ensemble soil loss quantiles in each grid cell were classified based on the soil loss levels that were used in Fenta et al. (2020) and their area proportions were summarized. Overall, the area proportions of the median soil losses agree with the findings of Fenta et al. (2020). It is, however, evident that the area proportions of the soil loss levels that were calculated for the lower and upper quantiles strongly differ from the proportions presented in Fenta et al. (2020). While the lowest two quantiles of the USLE ensemble calculated a *very slight* soil loss for over 90 % of both countries, the maximum soil losses calculated in each grid cell would result in *very high* soil loss for almost 70 % of the area in Uganda and over 40 % of the area in Kenya (compared to the 4 and 5 % shown in Fenta et al. (2020) and the 3 % shown by the ensemble median).

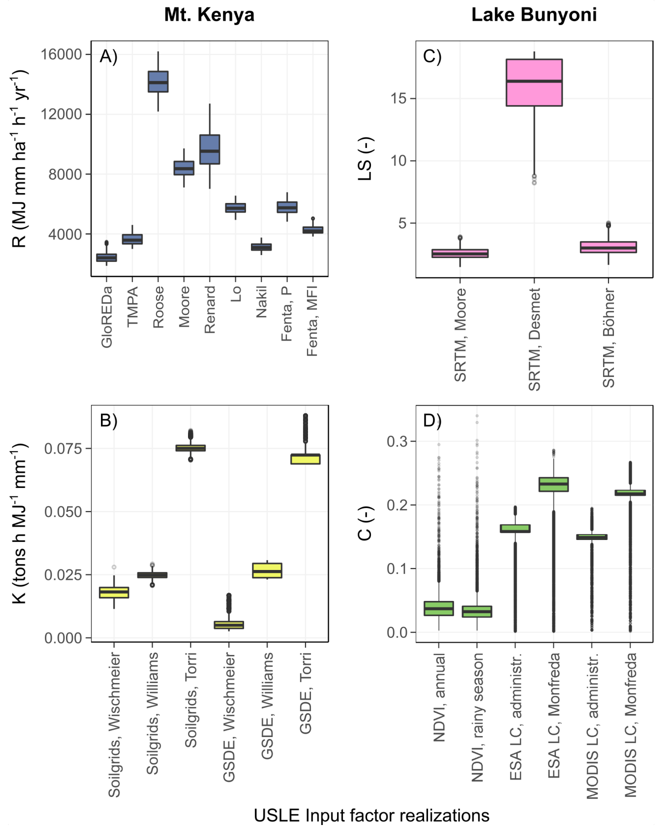

Figure 7. Variability between the realizations of the most important USLE model input factors. The cases A) to D) (delineated in Fig ~~8~~6) exemplify the differences in the distributions of the input factor R, K, LS, and C, respectively. The cases A) to D) include the values of input factor realizations for grid cells, in which the respective input factor was the most sensitive one and the majority of models of the model ensemble predicted high to severe soil loss~~was predicted to be likely~~. Panel A) analyzes the R factor realizations at the top of Mt. Kenya, panel B) shows the differences in the K factor realizations in the belt around Mt. Kenya, and the panels C) and D) analyze the LS and C factors in the hilly topography of the Lake Bunyoni region.

The selected administrative units in Uganda and Kenya are located in erosion prone areas (shown in Fig. 3 and Fig. 4). ~~Averaging~~ Although, averaging the soil loss for the domain of an administrative unit reduces the impact of areas with excessive soil loss~~. Nevertheless~~, the median values of mean soil loss for the selected administrative units that result from the USLE model ensemble result in a moderate (blue) soil loss in 22 of the 27 administrative units. Four administrative units show even a high (yellow) mean soil loss, while only one administrative unit resulted in a ~~tolerable~~ slight (green) soil loss (Fig. ~~7~~ 9 a)). Particularly large mean soil losses were found for the administrative units Kabale and Kisoro in the Lake Bunyoni region and the administrative units Kasese and Bududa on the slopes of the Ruwenzori Mountains and Mt. Elgon, respectively. The data points shown as coloured squares in Fig. ~~7~~ 9 a) provide a reference to the soil loss assessment performed by Karamage et al. (2017) on district level in Uganda. As we included the realizations of the USLE input factors developed in Karamage

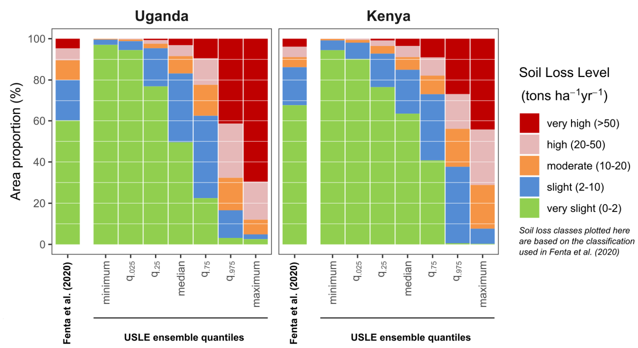

Figure 8. Comparison of the proportions of the areas in Kenya and Uganda that are summarized with different soil loss levels. The comparison shows the results reported in Fenta et al. (2020) to the results of the 972 USLE model realizations. The analyzed quantiles represent the soil loss quantiles in each grid cell that result from the USLE model ensemble. For the comparison the soil loss levels applied in Fenta et al. (2020) were used.

et al. (2017) in the present assessment, the calculated soil loss from Karamage et al. (2017) is a member of the USLE model ensemble. In 9 of the 16 districts the soil losses calculated by Karamage et al. (2017) are lower than the 25 % quantile of soil losses that resulted from the USLE model ensemble. Only for a few districts, such as Kasese, Bundibugyo, Nebbi, or Kaabong the soil losses calculated by Karamage et al. (2017) and the ensemble means show comparable values.

For each administrative unit, the mean soil losses that resulted from the individual USLE model ensemble members show wide spreads (indicated by box plots and light grey dots in Fig. ~~7~~ 9 a)). The spreads were particularly large in the administrative units with overall high soil losses. In all administrative units the mean soil loss that resulted from the individual USLE model setups are scattered over several soil loss classes (class boundaries indicated by dashed lines in Fig. ~~7~~ 9 a)). Fig. ~~7~~ 9 b) summarizes the numbers of model setups that predicted one of the four soil loss classes for each administrative unit. Although the median soil loss class for the majority of the administrative units is *moderate* on average ~~49 % (370 out of 756~~ 48 % (462 out of 972 models; with a range of ~~25.4 % to 60.4~~ 26.5 % to 61.2 % between the 27 administrative units) of the models from the USLE model ensemble predicted moderate soil loss, while all other model setups predicted one of the other four soil loss classes.

Fig. ~~7~~ 9 c) relates the soil loss classification in the selected administrative units to the average shares of the soil loss classes in the administrative unit areas. While on average only 20 % of the models from the USLE model ensemble predicted a ~~tolerable soil loss in the administrative units almost 55~~ slight soil loss almost 54 % of the areas of the administrative units show on average a ~~tolerable~~ slight soil loss. Areas with high and severe soil loss share only small areas in the administrative units with average fractions of ~~14.5 % and 6.5~~ 14.9 % and 7.1 %, respectively. Though, these areas have a strong impact on the mean soil loss in an administrative unit.

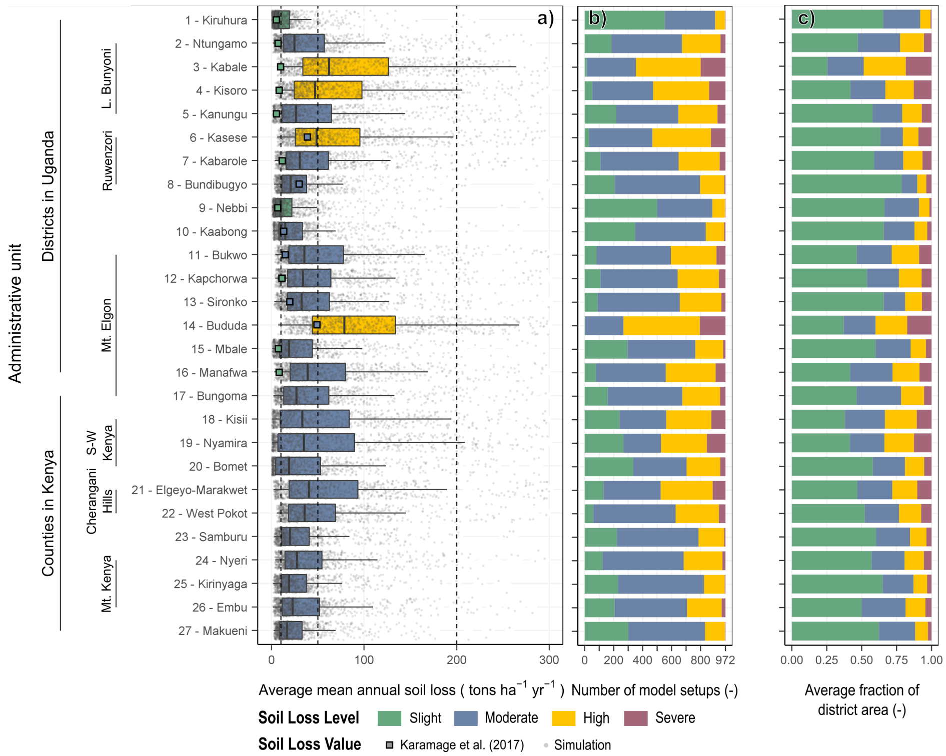

Figure 9. Mean soil loss in selected erosion prone administrative units of Uganda and Kenya. Panel a) shows the mean soil loss from all ~~756~~ 972 USLE realizations in the selected administrative units with grey dots and aggregated as boxplots. The colors indicate whether the median soil loss in an administrative unit is ~~*tolerable*~~ *slight* (green), *moderate* (blue), *high* (yellow), or *severe* (purple). For comparison the results from Karamage et al. (2017) are plotted as colored squares. Panel b) shows the distributions of soil loss levels that were predicted by the USLE model realizations for the selected administrative units. Panel c) shows the average shares of soil loss classes for the domains of the selected administrative units.

4.4 Comparison of the soil loss estimates to in field assessments

While the total ranges of the soil loss estimates calculated for the reference sites from the USLE model ensemble cover the reference soil losses from literature values in all five cases in Fig. ~~6~~ 10 the interquartile ranges for the USLE model ensemble can strongly differ from the values that were estimated from in field experiments.

Cases I and II in Fig. ~~6~~ 10 compare average soil losses for the domains of the villages Iguluibi and Waibale to soil loss assessments of small scale farm compounds. In both cases the soil losses assessed in the field exceed the interquartile ranges that result from the USLE model ensemble, with ranges of 56 to 460 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ and ~~8.6 to 53.4~~ 6.5 to 40.4 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ in Iguluibi and 27 to 135 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ and ~~3.1 to 16.2~~ 2.8 to 10.2 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$ in Waibale.

For the Sinje test case (case III in Fig. ~~6~~10) in the Manafwa district in Uganda Bamutaze (2010) resulted in very low soil losses between 0.185 and 1.761 $\mathrm{tons\ ha^{-1}\ yr^{-1}}$. Generally the districts along Mt. Elgon are known to be erosion prone. On average the USLE model ensemble predicted high soil loss for the location of the Sinje test catchment with a median soil loss

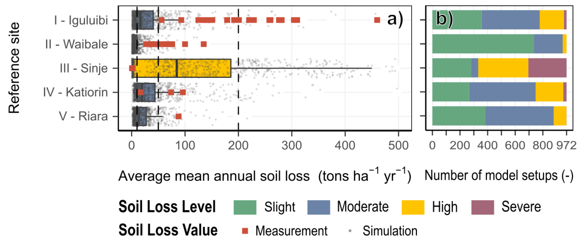

Figure 10. Comparison of soil loss simulations from the USLE model ensemble to in field soil loss assessments acquired from selected studies. The reference soil loss values are shown with red squares for the sites Iguluibi and Waibale (De Meyer et al., 2011), Sinje (Bamutaze, 2010), Katiorin (Sutherland and Bryan, 1990), and Riara (Kithiia, 1997) in panel a). The soil loss simulations for the reference extents from all ~~756~~ 972 USLE model realizations are shown as grey circles. Corresponding boxplots show summary statistics for the model ensembles in panel a). Panel b) summarizes the numbers of models that predicted the soi loss levels ~~*tolerable*~~ *slight* (green), *moderate* (blue), *high* (orange), and *severe* (purple) for the reference sites.

~~86.8~~ 97.29 tons ha^{-1} yr^{-1} and an interquartile range between ~~3.9 and 212~~ 3.7 and 228 tons ha^{-1} yr^{-1}. Although the range of calculated soil losses is generally large, only 11 % of models from the USLE model ensemble predict soil losses that are in the range of the values reported by Bamutaze (2010).

The reported soil losses for the Katiorin catchment are comparable to the soil loss estimations for the catchments extent that resulted from the USLE model ensembles (case IV in Fig. ~~6~~10). Sutherland and Bryan (1990) reports a range of soil loss between 16 and 96 tons ha^{-1} yr^{-1} for the Katiorin catchment and ~~21~~ 47 % of the USLE model setups predict a soil loss in the same range. Almost ~~30~~ 44 %, however, result in soil losses lower than 16 tons ha^{-1} yr^{-1}.

Kithiia (1997) reports a very low soil loss of 0.36 tons ha^{-1} yr^{-1} for the Riara Basin. All USLE model realizations predict larger soil losses for the domain of Riara, with a minimum value of ~~1.6~~ 1.4 tons ha^{-1} yr^{-1} and an interquartile range of ~~6.8 to 30.7~~ 6.3 to 27.4 tons ha^{-1} yr^{-1}.

5 Discussion

5.1 ~~What can we learn from such an analysis~~

~~We illustrated how drastic the differences in~~

With this study we illustrated how strongly the estimated soil loss magnitudes can ~~be by selecting a method to calculate a USLE input factor~~vary, simply due to the choice of the methods and data that are implemented to calculate the USLE input factors. The statistical analysis of the generated USLE model ensemble (Fig. 3) showed that ranges of one or two magnitudes for the estimated soil loss were possible. These large ranges ultimately ~~result from~~ resulted from the differences in the individual realizations of the USLE input factors (some realizations were over a magnitude larger than others in Fig. ~~9~~7 and the tables S.11 – S.14). These differences in the inputs propagate through the USLE equation by multiplication ~~.~~

~~The~~ (Sonneveld and Nearing, 2003). The large uncertainties in the estimation of soil loss that result from such an ensemble approach, but also the effort that has to be put into such an analysis raise immanent question that ~~arises is whether we are able to exclude any combinations of USLE input factors or individual realizations of input factors, as they fail to result in plausible soil losses and eventually reduce the ranges in estimated soil losses (Beven, 2018; Beven and Brazier, 2011). From a modellers perspective, neither the comparison to observations (Fig. 6) , nor a plausibility check of the individual USLE model realisations generally allowed us to exclude model combinations or individual methods for the generation~~ will be discussed in the following: i) what are the benefits of such an ensemble soil loss assessment and what can we learn from a comparison to single model soil loss studies; ii) can we identify specific realizations of the input factors and USLE model combinations as implausible, exclude them from the model ensemble and eventually reduce the uncertainties in the ensemble model predictions; iii) what can we delineate from the importance of USLE inputs ~~. As a consequence, we have to acknowledge the uncertainties that result from commonly used methods to generate spatially distributed estimates of the USLE input factors and /or find additional ways to evaluate the simulated soil losses (see section 5.4)~~on the estimation of soil loss and how do these findings compare to other studies; iv) and are in-field data that are potentially available from monitoring studies a valid reference for the evaluation of large scale USLE soil loss assessments.

~~In the case that model setups cannot be falsified and are considered as "fit-for-purpose" (Beven, 2018), we must treat each member of the ensemble equally. In Fig. 4 and~~

5.1 Ensemble soil loss modeling - How can we benefit from the collective

Although the calculated magnitudes and the ranges in soil loss that result from the model ensemble were extreme for some locations, the ensemble modelling approach can provide essential information on the overall simulation uncertainties that are simply not available from single model implementations. The analyses illustrated in Fig. 5 ~~, and Fig. 7 we proposed ways to utilize the generated~~ exemplify how we can utilize the information provided be the USLE model ensemble ~~and infer the severity of soil loss on different spatial levels based on a compromise of many models. From a decision makers perspective, such large ranges in soil loss imply challenges in the interpretation of the results and complicate decisions on possible measures that can be implemented. Nevertheless, the analysis of soil loss on the administrative level (~~to qualitatively evaluate the erosion risk for a specific location. Such a visualization can greatly support decision making as it provides in addition to the soil loss level information whether the majority of the USLE model ensemble predicted that specific soil loss level, or whether the prediction is highly uncertain. In the specific example in Fig. 5 low soil loss levels were frequently classified by a large majority of the USLE ensemble, while in complex terrain and for more severe soil loss levels a stronger disagreement between the USLE ensemble members is visible. In such cases, however, the combination with summary statistics as illustrated in allow an evaluation of the erosion risk as well as the uncertainties in the prediction.

The comparison to the results presented in Fenta et al. (2020) and Karamage et al. (2017) greatly exemplifies the issues that may arise from a single USLE model soil loss assessment. While the results presented in Fenta et al. (2020) show a good comparison to the ensemble median the results of Karamage et al. (2017) are substantially lower than the ensemble predictions. These circumstances can be explained to a large extent due to the selected methods that were implemented to calculate the USLE input factors in the two studies. Fenta et al. (2020) employed for example the method of Panagos et al. (2015c) to calculate the C factor, which was found to be less sensitive to extremely low C values in densely vegetated areas compared to the method of Van der Knijff et al. (2000) (see Fig. 7 ~~) and particularly the comparison to the results from Karamage et al. (2017) should highlight an example to favor the analysis of the entire possible uncertainty range in soil loss, as opposed to accepting a single prediction of soil loss as a basis for decision making.~~ D)). The method of Fenta et al. (2017) that was used to calculated the R factor in Fenta et al. (2020) resulted in an R factor realization that was in the medium range in this study. As a consequence, the overall soil loss estimations also compared well to the ensemble median. Karamage et al. (2017) in contrast, employed the methods of Lo et al. (1985) to compute R and the method of Van der Knijff et al. (2000) to caculate C. Both methods were found to be on the lower ends of the spectrum when compared to the other methods in this study (particularly for the C factor in the densely vegetated regions of Uganda). In addition, Karamage et al. (2017) implemented a global P factor value that further reduced the soil loss estimates. As a consequence, the calculated soil loss estimates were low in general. While, the ensemble approach allows to compare each model combination to all other combinations and therefore provides a reference point to the implementation of a specific USLE input combination, a single model approach simply cannot provide such information.

~~A possible approach to utilize the USLE ensemble predictions was presented in the combined assessment of soil loss levels that were predicted by the majority of the ensemble members and showed the fraction of models that predicted dominant soil loss levels~~

5.2 USLE input realizations - Ranges, plausibility, and their comparison to other studies

The analysis and comparison of the USLE input realizations revealed several systematic patterns in their summary statistics calculated for the entire study area, but also in the four specific cases that were presented in Fig. ~~4. Such reduction of information provided by the ensemble resultsenables to provide a "single" answer to the question of the severity of~~ 7. Some of the ~~soil loss to be expected and conveying the "certainty" of a prediction at the same time. Though, thresholds that define a specific soil loss as tolerable, or critical are seen as controversial (Bosco et al., 2015) and~~ patterns in the differences between specific realizations that were observed in the specific cases agreed with the patterns for the entire study domain, while others showed contradicting results. The systematic differences in the K factor realizations for instance were found in the specific case in Fig. 7 B), while the cases A) and D) for instance showed opposite behaviors of the realizations of R and C for the smaller regions. Overall, the sets of realizations for each input resulted in wide ranges of values that eventually resulted in large ranges of the calculated soil loss. Thus, it is worth to put the input factor realizations into a reference to other studies. In any case, we have to keep however in mind that a ~~wide range thresholds for tolerable soil loss (e.g., Karamage et al., 2017; Bosco et al., 2015; Bamutaze, 2015; Blanco-Canqui and Lal, 2008; Montgomery, 2007) and soil loss classification schemes (e.g., Zachar, 1982; FAO-PNUMA-UNESCO, 1980) are proposed.~~ comparison to other studies does not per se determine specific realizations to be more or less plausible, as other large scale soil erosion studies face the same issues in terms of a model validation (see 5.4).

~~To illustrate the dominant soil loss level together with the frequency of models that predicted that soil loss level can strongly support the evaluation of the model results . A large share of the USLE input factor combinations, for instance, predicted low soil losses along slopes with dense forest vegetation (see e. g. dark green area in Fig. 5 d)). Thus, reduced soil loss in densely vegetated areas can be expected with a higher certainty based on the ensemble predictions. In contrast, areas with sparse vegetation (e.g. close to the summit of Mt. Kenya~~ Locally the calculated R factor realizations showed values of large maximum values, where the largest R values were found for the realizations R_{TMPA}, R_{Renard}, and R_{Roose} with maxima of 31068, 25755, and 22741 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$, respectively. The third quantiles of all methods range, however, between 2046 and 9636 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$. Other large scale studies in East Africa and on a global scale report also wide ranges in the R values. In an assessment for East Africa Moore (1979) calculated rainfall erosivities of up to 10900 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ for the Mt. Elgon region. Fenta et al. (2017) found high values for R of > 7000 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ for the northwestern Ethiopian highlands, the area around Mt. Kilimanjaro, and the western region around Lake Victoria in Uganda. Fenta et al. (2017) found these results to be in line with the findings in Vrieling et al. (2010). Karamage et al. (2017) calculated a range of 1674 – 6358 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ for Uganda. For Europe Panagos et al. (2015a) found a range for R of 51.4 – 6228.7 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$. In a global soil loss assessment Naipal et al. (2015) calculated values for R that exceeded magnitudes of $1 \cdot 10^5$ $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$. Although Naipal et al. (2015) emphasize that such large values are unrealistic they stress that erosivities of over 20000 $\mathrm{MJ\ mm\ ha^{-1}\ h^{-1}\ yr^{-1}}$ can be observed in the tropics, which is also reported in Panagos et al. (2017). The excessive R values that are shown locally by a few of the implemented realizations of R can be questioned. Overall however, the ranges of the individual R realizations are in line with the results reported in other studies.

In the specific case presented in Fig. 7 B) the K values that were calculated with the method of Torri et al. (1997) showed maximum values of 0.088 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$. For the entire study region values larger than 0.1 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ were found. Depending on the input data set (Soilgrids250m or GSDE) the methods of Wischmeier and Smith (1987) and Williams (1995) resulted in maximum values of 0.038 and 0.039 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$, and 0.055 and 0.052 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$, respectively. Ranges of K factor values that are shown in other studies show comparable values to the ranges that resulted from the methods of Wischmeier and Smith (1987) and Williams (1995). The implementation of the method of Torri et al. (1997) exceeds the ranges shown in other studies. Karamage et al. (2017) calculated a range for K of 0.015 – 0.029 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ for Uganda. A similar range is shown in Fenta et al. (2020) for East Africa with high erodibilities shown for the North-West of Lake Victoria and the Rift Valley and the area around Lake Turkana in Kenya. On a global scale, Borrelli et al. (2017) implemented K values that range from values lower than < 0.01 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ to values > 0.04 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$. For Europe Panagos et al. (2014) found values for the soil erodibility of up to 0.076 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ for medium to fine textured soils. Naipal et al. (2015) implemented values for K of 0.08 $\mathrm{tons\ h\ MJ^{-1}\ mm^{-1}}$ for highly erodible volcanic soils. As a consequence, the implementation of the method of Torri et al. (1997) as it was implemented in this study must be questioned.

The majority of erosion studies implemented the method of Desmet and Govers (1996) to calculate LS (e.g. Fenta et al., 2020; Karamag . As a consequence, the ranges for LS that were found in these studies are in line with the ranges for LS that we found with the implementation of the method of Desmet and Govers (1996). Although the methods of Moore et al. (1991) and Böhner and Selige (2006) showed excessive maximum values, these were highly local. As shown in the specific case in Fig. ~~5) show increased soil loss , but lower percentages of USLE model members that predict the respective soil loss level at the same time. These are potential zones where any form of validation or plausibility check would benefit the analysis~~7 C) large variations in the calculated soil loss were mostly found in locations where the method of Desmet and Govers (1996) resulted in large values for LS while the other two methods resulted in low values.

Overall, the C factor values reported in other studies are comparable to the ranges of the C factor that were calculated in this study, since the majority of studies which we reviewed implemented either the MODIS NDVI in combination with the method of Van der Knijff et al. (2000) to calculate C or employed the method of Panagos et al. (2015c) in their study regions. Thus studies that implemented the NDVI (e.g. Karamage et al., 2017) resulted in ranges for C factor of 0 – 1. Karamage et al. (2017) for example found values of $C < 0.05$ for large areas in the western and central parts of Uganda, whereas only regions in the North East show values > 0.2. Fenta et al. (2020), who implemented the method of Panagos et al. (2015c) calculated C values that range between 0.135 and 0.33 in the South West of Uganda and north of Lake Victoria, whereas the forested regions in central Uganda show values below 0.01. Both findings are reflected in 7 D), that documents the discrepancies between the two methods of Van der Knijff et al. (2000) and Panagos et al. (2015c). While the method of Panagos et al. (2015c) accounts for the agricultural areas in the South West of Uganda in the calculation of C, the method of Van der Knijff et al. (2000) only accounts for the vegetation density (by implementing the NDVI as a proxy).

~~The analysis of the~~

5.3 Input factor importance - Findings and comparison to other studies

Fig. 6 illustrated the most dominant USLE input factor realizations with respect to their impact on the uncertainties of the ~~simulated soil lossreveals patterns for the USLE inputs~~ calculated soil loss. The dominant input factors revealed spatial patterns on different spatial scales~~in Fig. 8. These~~. The patterns of the most dominant inputs follow the patterns of the input data that were employed to calculate the input factor realizations. Thus, the shown patterns can support in identifying the ~~USLE inputs that require greater attention for the USLE model setup, based on the local conditions~~input data/method combination that introduced the largest share of uncertainties in the calculation of soil loss locally. Larger patterns were mainly visible for the input factors C and K, while LS showed very small scaled patterns and R showed a lower relevance for the prediction uncertainties in general. While the C is ~~clearly~~ the most important input factor for large regions in the densely vegetated part of Uganda and around Lake Victoria in Kenya, K is most relevant in the drier regions of Kenya. The R factor was mainly relevant in higher altitudes. The LS factor realizations were most relevant in highly variable topographies and very flat areas where the factor is close to zero and numerical issues governed the results of the sensitivity analysis.

Based on nine nation wide soil loss data sets, including soil loss estimates for Europe (Panagos et al., 2015e), and the original USLE data set for the USA Estrada-Carmona et al. (2017) performed global sensitivity analysis to identify the dominant USLE input factors. In 8 out of 9 country wide analyses of the USLE input importance Estrada-Carmona et al. (2017) identified the C factor to be tho most relevant one for the soil loss estimation. The second most relevant input shown in Estrada-Carmona et al. (2017) was, however, the LS factor, that was identified to be relevant very locally in this study. In a study in the mountainous

Tongbai-Dabie region in China Zhang et al. (2013) also found that the LS factor was the most important input factor on small scales. Keyzer and Sonneveld (1997) performed a meta-model study and analyzed the USLE model relationship based on the original US data set that was employed in the development of the USLE. Based on the data points that were available from the US data set, Keyzer and Sonneveld (1997) concluded that larger uncertainties in the soil loss estimation can be expected for high R and LS values, as well as for high and low values for the K factor as the number of samples were low for these regions in the USLE inputs in the original USLE data set. Falk et al. (2010) employed Bayesian melding to quantify the uncertainties in the soil loss estimates and to identify the USLE inputs that contribute the most to the uncertainties for a catchment in Eastern Australia. In an analysis of the spatial distribution of the input uncertainties, and the magnitudes and uncertainties in the calculated soil losses Falk et al. (2010) found a relationship between the patterns of the S factor and the patterns that were observed in the calculated soil loss.

All studies that were reviewed here differ in their methodological approaches and also come to different conclusions with respect to the importance of the USLE inputs. Overall, the analysis of the most important inputs can greatly support a soil loss assessment in order to identify the dominant sources of uncertainties in the soil loss estimates. Yet, the importance of the the individual inputs seems to be very specific for the the individual studies.

5.4 Model validation - Are in-field data a valid reference for USLE model evaluation

~~No clear pattern can be defined~~ Although large scale meta-analysis studies exist, that provide soil loss data globally (García-Ruiz et al., 2015 , or for specific regions in the world (e.g. for Africa (Vanmaercke et al., 2014), or for Europe (Maetens et al., 2012)), these studies often compile reported soil losses that result from a wide range of study settings. The presented comparison of the USLE ensemble soil losses to in-field erosion studies should therefore not be seen as best practice, but rather provides illustrative examples of potential issues that can arise in the comparison to in-field data.

Overall, we were not able to delineate a clear pattern from the comparison of estimated soil losses to in-field soil loss assessments within the study domain~~. The~~ , as the selected reference studies had different specific scopes. While Sutherland and Bryan (1990), or Kithiia (1997) monitored the accumulated soil loss from river catchments, De Meyer et al. (2011) assessed the soil loss on small scales and on sites that are particularly erosion prone. While most of the selected reference studies report low to moderate soil losses for their study domains, De Meyer et al. (2011) reports high to excessive soil losses for several of the farm compounds they investigated. The methodologies that were used for the soil loss assessments strongly impacted the reported soil losses and result in wide ranges of soil loss between the selected studies.

Aforementioned limitations of the temporal and spatial representativeness of the reported soil losses from the selected reference studies are likely to be present and may have impacted the significance of the comparison to the soil loss estimates. At larger scales, processes other than the ones that are assessed by the USLE, such as deposition processes, gully erosion, or bank collapses have to be considered in the quantification of the soil loss (Govers, 2011). Boardman (2006) stresses that long-term monitoring schemes and additional assessments of rills and gullies would be required to allow a comparison to soil loss estimations. Records from erosion monitoring studies are, however, usually short (Evans, 2013; Govers, 2011). The reference studies of Sutherland and Bryan (1990) and Bamutaze (2010) for instance only covered monitoring periods of 1 and 2 years, respectively and thus are only snapshots in time that are difficult to compare with long-term assessments.

Apart from the short monitoring periods that are often available from reference studies it is likely that the (remote sensing) data that was employed to calculate the USLE input factors and to assess the soil loss do not reflect the conditions that were present during the monitoring period in a study region, simply because the monitoring period and the period for which input data are available do not overlap. Soil cover by vegetation perfectly illustrates the issue. Monitoring data can date back several decades (e.g. Sutherland and Bryan (1990) in our case). On large scales the vegetation cover is often estimated by employing remote sensing satellite data that can be more recent than monitoring data. Particularly, in East Africa deforestation affected the land cover over the past decades with reported decreases in the forest biomass of up to 26 % in Uganda (Jagger and Kittner, 2017) , or forest clearances in protected forests in the Mt. Elgon region of 33% (Petursson et al., 2013). In such a case, a C factor that was calculated with recent remote sensing data would fail to reflect the condition of the vegetation during the monitoring period.

Although the soil losses reported in De Meyer et al. (2011) are based on cumulative soil losses in farm compounds over periods of 15 to 20 years, the spatial domains of the farm compounds that were analyzed do not properly reflect the spatial resolution of the grid on which the soil loss assessment with the USLE was conducted. Other reference studies, such as Sutherland and Bryan (1990) or Kithiia (1997) ~~better meet~~ represent the average soil loss at the catchment scale. One could assume that the spatial scale of ~~the USLE~~ such studies better agrees with the spatial scale of a large scale soil loss assessment ~~. However, the presented soil yields are in-stream sediment loads~~with the USLE. These reported loads are affected by processes, such as deposition, gully erosion, land sliding, or bank erosion that superimpose rill and inter-rill erosion (Govers, 2011). Boardman (2006) further highlights that the in-stream sediment delivery ratios (SDR) are a function of time and scale. Boardman (2006) compares the differences in the SDR of the Yellow River and British rivers that differ by a factor of 28. Such large difference in the SDR does, however, not necessarily reflect the differences in soil erosion rates.

Evans (1995) and Boardman (2006) point out that soil losses derived in plot scale experiments do not reflect erosion taking place on the landscape scale. Evans (1995) found that plot scale soil losses are larger than soil losses in the landscape by a factor of two to ten under comparable conditions. The soil losses reported in Bamutaze (2010) were however lower than the soil losses estimated by almost 90 % of all used USLE models in this study and thus show an opposite behavior.

Prasuhn et al. (2013), Warren et al. (2005), or Evans (2002), among others, demand that soil losses that were estimated by models must be supported by field based observations. Bosco et al. (2015) emphasize the limitations of in-field validation for large scale studies. Bosco et al. (2014) and Bosco et al. (2015) highlight the potential to employ ~~new~~ high resolution satellite imagery and Google Earth, or Google Streetview data for plausibility checks of soil loss estimates. Yet, the verification (and falsification) of the absolute magnitudes of soil loss estimates on large scales remains a challenge.

5.5 Further considerations and limitations

In this study we only implemented a selection of methods and primary data sources for the calculation of the USLE input factors. Hence, we have to recognize that the performed study does not provide a comprehensive picture of the uncertainties that are introduced by different representations of the USLE input factors. Albeit, the calculated ranges in soil loss were substantial and considering additional realizations of USLE input factors can in the worst case increase the ranges of calculated soil loss. The demonstrated procedure, however, pinpoints the central weakness of the USLE. The model can identify relative risks for soil erosion, but fails to predict exact magnitudes of soil loss. Eventually every modeller must acknowledge the limitations of the USLE (some of them we addressed at great length) and not overestimate the predictive power of the model.

We are fully aware that such a comprehensive analysis is very likely out of scope for most studies that employ the ~~ULSE~~ USLE model, as in most applications the soil loss estimation is only a small part of the entire analysis. Further, extending such analysis to larger domains or increasing the spatial resolution can be limited by available computation and storage capacities. For instance, the entire ensemble of USLE model representations in the present study comprised ~~$11225 \times 14778 \times 1512$ (~$250 \cdot 10^9$~~ $11225 \times 14778 \times 1944$ (~$322 \cdot 10^9$) pixel values required ~~2.13~~ 2.74 TB distributed in SQlite data bases on four separate hard drives to allow an efficient batch-wise analysis of the model results. ~~Nevertheless, checking the plausibility of estimated soil loss must be the minimum requirement for every study employing the USLE (see suggestion above and Bosco et al., 2015, 2~~ ~~.~~

We omitted the analysis of the conservation support or management practice factor P in this study. For all USLE model setups the P factor was globally set to a value of 1. According to literature values, the application and maintenance of support practise measures can substantially reduce the soil erosion in erosion prone landscapes. Conservation measures, such as contour farming, strip cropping, or terracing reduces the calculated soil loss by a factor of up to 2, 4, and 10, respectively, depending on the slope on which the measure was applied ~~(Karamage et al., 2017)~~(Karamage et al., 2017; Shin, 1999). Large scale estimations of P and the implementation of the P factor in large scale soil loss assessments are almost absent, as only very limited spatial data is available on soil conservation measures. Panagos et al. (2015d) generated a spatial estimate for P for entire Europe, considering the effects of contouring, stone walls, and grass margins. Panagos et al. (2015d) thereby used comprehensive spatial statistics on soil conservation based on 270000 data points available for Europe from the LUCAS data base (LUCAS, 2012). Such detailed data is, however, not available in all regions of the world. Thus, other large scale assessments omitted the P factor and used a value of 1 globally (e.g., Borrelli et al., 2017), assigned a reduced P value globally in the study domain (Karamage et al., 2017), ~~or~~ assigned global values for P to specific land uses (Yang et al., 2003), or used land cover and slope as a proxy for the P factor estimation (Fenta et al., 2020). Such simplifications do not reflect the spatial distributions of soil conservation measures that are actually applied in a (large scale) study domain, although their impact on large soil loss estimates can be substantial.

6 Conclusions

The USLE model, an empirical model to estimate the soil loss by water erosion is widely applied in large scale assessments and was implemented in a case study to assess the soil loss on the entire domain of Kenya and Uganda. Although the USLE has a simple model structure and is therefore easy to implement, the generation of spatially distributed estimates of the USLE input factors for the study domain poses a major challenge. Large scale (remote sensing) data products and methods to employ them for the generation of the USLE inputs greatly support soil loss assessments on large scales. ~~In order to analyze and quantify the impact of available data products and with methods for the calculation of USLE inputs on the uncertainties of estimated soil losses, we generated a range~~ We generated sets of realizations for each USLE input factor and combined them to ~~756 realizations of the USLE~~ 972 USLE model setups to compute spatially distributed soil loss ~~for entire~~ estimates for Kenya and Uganda. Based on the generated USLE model combinations we analyzed and quantified the impacts of frequently used methods to calculate USLE inputs on the uncertainties in the soil loss estimation with the USLE model.

Overall, but particularly in erosion prone areas of the study domain, the calculated ranges of soil loss showed large values. In many cases, especially in areas with high soil losses, the calculated ranges exceeded the mean soil loss by greater than one order of magnitude. To condense the information provided by the USLE model ensemble we proposed to classify the soil loss into the soil levels ~~*tolerable*~~*slight*, *moderate*, *high*, and *severe* employing common soil loss thresholds from literature. The classification allowed to utilize the USLE ensemble predictions to analyze but consider the "certainty" of the prediction simultaneously. The employed approach enabled to identify zones with ~~increased~~ a high soil loss, but also areas where the agreement in the USLE model ensemble is low and thus suggest an evaluation and/or plausibility checks for the simulations.

A sensitivity analysis of the soil loss predictions was performed to identify the USLE input factors that introduce the strongest impact on the uncertainties of the soil loss estimates. The analysis identified clear patterns on the large scale for the input factors C and K, where the C factor is more relevant for areas with denser vegetation and the K factor showed a greater importance for the calculation of the soil loss in dry less densely vegetated areas. The LS factor showed very scattered patterns in complex topographies and was relevant for the uncertainties of the calculated soil loss in sloped terrain.

The comparison of the USLE ensemble soil loss estimates to single USLE model implementations illustrate the advantages of an ensemble over single model studies. While the ensemble members provide a reference to other USLE input combinations, with a single model no reference is given to evaluate the calculated magnitudes in soil loss.

A validation of simulated soil loss on large scale domains, employing in-field assessments from the literature poses to be a challenge and in this study no clear conclusions can be drawn for the ensemble soil loss estimates when they were compared to soil loss observations. Thus, the comparison failed to falsify any of the generated USLE model combinations that would allow to exclude ensemble members to ultimately reduce the soil loss prediction uncertainties. Major issues for a valid comparison are the differing origins of the in-field soil loss data as well as spatial and temporal limitations of the observed data.

Although available computational and time resources will naturally limit such an analysis of soil loss predictions in most studies that employ the USLE model, the findings clearly highlight the importance to critically view and analyze single USLE model predictions, as the resulting soil loss estimates are highly sensitive to the combinations of realizations of the USLE model inputs. We further question the aptitude of soil loss assessments based on in-stream sediment yields or small scale plot experiments to be valid data for the evaluation of soil loss estimates~~and want to refer to new approaches (e.g. Bosco et al., 2014) that potentially allow~~. We should think of new approaches to validate soil loss estimates that employ large scale data that is now available. Bosco et al. (2014) outline a method to employ satellite imagery to check the plausibility of large scale soil loss assessments.

Code and data availability. The study was performed using openly available primary input data. For some of these data we do not have the permission for further distribution. All input data can, however, be acquired from the rights holders of these data sets. All intermediate and final data that were generated in this study and the corresponding R code to manage and process the data are available upon request to the corresponding authors.

Author contributions. CS and MH designed the study and acquired and processed the input data. CS performed all analyses. MH and CS prepared the figures. KS and JK contributed in the methodological framework. CS, MH, BM, JK, and KS compiled the manuscript.

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

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