

Reviewer#1

We sincerely thank reviewer 1 for their valuable comments on this manuscript. We have tried our best to incorporate all suggestions. Detailed answers to the specific questions are given in the following paragraphs.

Comment 1: Page 2, the main objective of the manuscript is presented in lines 10-12. However, there are repeated detailed objectives below. I would suggest a more clear structure for the Introduction section.

Response 1: The objective present in page 2, lines 10 - 12 *“The main objective of this work is to present a methodology to quantify uncertainties in SE and SY for ungauged basins using commonly used models and easily accessible datasets.”* emphasises the importance of this research and explain its usefulness to readers.

Action: Specific objectives of the study are stated in page 5, line 5 - 10. As suggested by the reviewer, we have removed lines 10-12 in page 2 and tried to avoid any repetitions in the revised manuscript.

Comment 2: As for R in RUSLE, is it a rainfall and runoff erosivity factor according to the original model concept?

Response 2: Yes, R factor is used as rainfall and runoff erosivity factor according to the original model concept proposed by Wischmeier and Smith (1978).

Comment 3: In page 5, line 26, the discharge and sediment load records for 16 years are available at the stations. The manuscript should give more details on model calibration and validation.

Response 3: Sediment load records for Husepur gauging station (HSG) and Nanak sagar dam (NSD) are available for 16 and 40 years, respectively. RUSLE model was originally proposed to apply for long term (> 20 years) soil erosion estimation (Wischmeier, 1959; Nearing et al., 2017). Hence we have validated our model with average sediment load at NSD and HSG during the observation period. The results are presented in Figure 8, page 31.

Comment 4: There is a large reservoir built in 1962, which may play an important role in sediment trapping. The sedimentation rate data can be used for sediment yield calibration. The SDR should also consider the effect of reservoir trapping, though the model is empirical.

Response 4: Yes, Nanak Sagar reservoir has a significant effect on sediment trapping (6.4×10^5 tones/year). We have incorporated the effect of reservoir on soil erosion and sediment yield estimation by using the methodology proposed by Sharda and Ojasvi, 2016. Gross soil erosion for the Garra basin is estimated by extracting the area covered by the reservoir. It is called as gross soil erosion for free basin area (Total basin area – reservoir basin area). The gross soil erosion for free basin area and SDR are used to estimate sediment yield at Husepur.

Comment 5: When compared the annual rainfall and rainfall erosivity, I found the R factor is much lower than the regions with similar rainfall amount, I doubt the proposed the method for R estimation. As well, the very coarse rainfall data might be the dominant factor influencing the simulation results, rather than the R factor itself.

Response 5: In this study, we selected equation proposed by Babu et al. (1978) that was developed using the rainfall data from various meteorological stations in India (Eq. a in Table 2 in the manuscript). This equation is based on the linear regression between annual average rainfall amounts and R factor. Originally, this equation was proposed to estimate R factor in meter tonnes cm / ha hr unit which needs a multiplication factor of ‘9.8’ to convert into MJ mm/ ha hr unit (Foster et al., 1981). We had missed this factor in our estimate. After revision, we have incorporated the updated value of R factor and revised the subsequent results.

Action: Revised R factor are given in Table 1 and shown in Figure 4(a) in the revised manuscript.

Please also see our response to comment 7.

Comment 6: Soil map is rough too, I would suggest to do a field survey for sampling, or obtain a relative detailed soil data.

Response 6: We have used NRSC soil data (1:50,000; 25 m), which is described in Table 1, page 23. This is the best soil dataset available for this region in terms of spatial resolution and is based on field surveys. Obtaining new field survey data for the study area will be repetitive, cumbersome and outside the scope of this study. We have re-classified the soil map into soil textural classes, namely loam, sand and sandy loam (Figure 2 (c), page 26) which is why it looks rough. On the other hand, this dataset has 11 soil classes (shown in Figure 1(b) below), and for each class, K factor is estimated.

Comment 7: As for LS factor, the maximum value is around 2500, this is extremely high due to the high gradients. This means the LS factor may be overestimated for the steep area, since the RUSLE model was originally developed for estimating soil erosion in relative gentle arable land.

Response 7: Yes, LS factor cannot be so high. It was a plotting error which has been corrected. Further, we have improved the value of slope length exponent (m). In the previous version, the exponent is estimated assuming rill to interrill ratio (β) as 0.67. In the revised version, β is estimated based on basin median slope (Morgan, 2016; McCool et al., 1997), which changed m from 0.40 to 0.14. The resulting LS factor is shown in Fig 1(a) below and its range is given in Table 1.

Table 1 compares the earlier and revised estimates of R and LS factors, and soil erosion. Table 2 presents the revised estimates of sediment yield at Nanak sagar dam (NSD) and Husepur gauging station (HSG). Compared to the earlier estimates, the revised estimates are closer to observed sediment yield at both the locations.

Action: LS factor values has been updated in the revised manuscript and updated figure is shown in Figure 4 (c).

Comment 8: When I saw the data listed in Table 2, the resolution for different data may cause high uncertainties for modeling results. The resolution of the spatial data highly influence the data quality, such as LS factor, K-factor, C and P factor.

Response 8: Yes, due to variation of resolution of different data may produce uncertainty in the modelled results. In this work, we have tried to estimate and propagate the uncertainty using easily available and most commonly used dataset for the Indian region in soil erosion and sediment yield prediction.

Action: It has been added in the “Limitation” section of the revised manuscript.



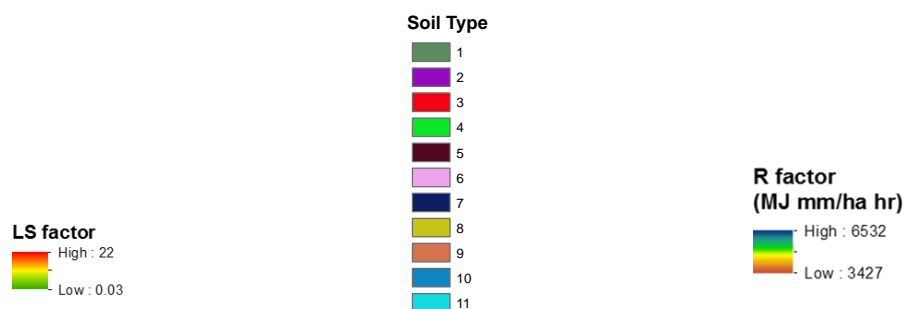


Table 1 Earlier and modified R, LS and soil erosion values

Factor	R factor (MJ mm/ha hr year)		LS factor		Soil Erosion (t/ha/year)	
	Earlier	Revised	Earlier	Revised	Earlier	Revised
Minimum	666.5	6532	0.09	0.03	0	0
Maximum	349.7	3427	53	22	1356	1423
Mean	467.3	4579.5	5.4	0.6	20.4	23

Table 2 Earlier and modified sediment yield values (units)

Station	Observed	Earlier	Revised
Nanak Sagar	6.4×10^5	8×10^5	6.9×10^5
Husepur	7.2×10^6	7.9×10^6	6.7×10^6

References:

Babu, R., Tejawani, K. G., Agarwal, M. C., & Bhushan, L. S. Distribution of erosion index and iso-erodent map of India. *Indian Journal of Soil Conservation*, 1978.

Foster, G. R., McCool, D. K., Renard, K. G., & Moldenhauer, W. C. Conversion of the universal soil loss equation to SI metric units. *Journal of Soil and Water Conservation*, 36(6), 355-359, 1981.

McCool, D.K., Foster, G.R. & Weesies, G.S. Slope length and steepness factors. In Renard, K.G., Foster, G.R., Weesies, G.A., et al. (eds), *Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE)*. USDA Agricultural Handbook 703, 1997.

Morgan, R. P. C., & Nearing, M. (Eds.). *Handbook of erosion modelling*. John Wiley & Sons, 2016.

Nearing, M. A., Yin, S. Q., Borrelli, P., & Polyakov, V. O. Rainfall erosivity: An historical review. *Catena*, 157, 357-362, 2017.

Sharda, V. N., & Ojasvi, P. R. A revised soil erosion budget for India: role of reservoir sedimentation and land-use protection measures. *Earth Surface Processes and Landforms*, 41(14), 2007-2023, 2016.

USDA. Sediment sources, yields, and delivery ratios. *National Engineering Handbook, Section 3 Sedimentation*, 1972.

Wischmeier, W.H. A rainfall erosion index for a universal soil loss equation. *Soil Sci. Soc. Am. Proc.* 23, 322-326, 1959.

Wischmeier, W. H., & Smith, D. D. Predicting rainfall erosion losses. *Agricultural Handbook no. 537*, US Department of Agriculture. Science and Education Administration, 1978.

Reviewer#2

We sincerely thank reviewer 1 for their valuable comments on this manuscript. We have tried our best to incorporate all suggestions. Detailed answers to the specific questions are given in the following paragraphs.

Comment 1: Page 6: Line 20-24: How the spatial variability of rainfall is taken into account. Since the measured rainfall data is from stations, which interpolation method was adopted to spatially distribution the rainfall data for each grid.

Response: We have used gridded rainfall dataset developed by India Meteorological Department (Rajeevan and Bhate, 2009). The dataset is available at 0.25 degree resolution and is obtained by interpolating more than 4,000 measured rainfall stations data using Shepard's interpolation method (Shepard, 1968).

Comment 2: Section 3.4: Step by Step procedure: is not a methodological step. Probably the sentence can just continue without the section.

Action: As suggested, we have removed this section heading in the revised version of the manuscript.

Comment 3: 4.1.1: Figure 4(a) suggest the highest rainfall value as 666 mm whereas in the text it indicates 1000 m. please check.

Response: Figure 4(a) is the rainfall erosivity map which is estimated by using average annual rainfall values. The values are reported in MJ mm/ha hr y units. In the text (page 10, line 25), we have reported that in upper mountainous region of the study area the average annual rainfall exceeds 1000 mm. To avoid any confusion, we have now prominently shown the units of R factor in Figure 4(a).

Comment 4: Section 5: The description indicates that uncertainty arising from input sources. In this study, such as R, LS, K and CP are not quantified. Out of 6 variables in SE equation, four are not considered. Similarly, the text indicates that model uncertainties are considered (and immediately suggest structural uncertainty could not be quantified). In my opinion, model uncertainty is structural uncertainty (they are the same thing). So, it appears that the paper is unable to take into account many variables of uncertainty assessment. In such circumstances, I don't see a good justification for the title of the paper which highlights uncertainty estimations.

Response: We have quantified uncertainty for all six factor of RUSLE. These uncertainties can stem from data (measurement errors, coarse spatial and temporal resolution, missing values), model (parameter uncertainty, structural uncertainty, algorithmic or numerical uncertainty), and stochastic nature of the soil erosion process. Structural uncertainty is part of model uncertainty (Beven and Brazier, 2011). However, in this study, we have used easily available uncertainty for different factors (Page 2, Line 9 – 11; Page 13, Line 4 – 7).

Comment 5: The second paragraph of section 5 Limitation is explaining very generic limitation of data and linked to uncertainty. This needs revision and I suggest not to highlight this kind of uncertainty which is there any way (such as DEM and RUSLE equations).

Action: Agreed. We have removed the concerned lines from section 5 in the revised manuscript.

Comment 6: In concluding remarks: various points describing findings be avoided and major conclusions can be highlighted.

Action: We have renamed section 6 as ‘Summary and Concluding Remarks’ and have highlighted the major conclusions from this study.

Comment 7: Abstract: page 1, Line 22: “Furthermore, the topographic steepness (LS) and crop practice (CP) factors exhibit higher uncertainties than other RUSLE factors.” However, In the main text, R, LS, K and CP are not quantified for uncertainty analysis. Please check the consistency.

Response: Uncertainty assessment has been done for all six factors of RUSLE equation (Please see response to comment 4). Thereafter, uncertainty comparisons suggest that LS and CP factor exhibit higher uncertainty.

Comment 8: Page 2: Line 5-6: the ‘uncertainties’ is mentioned in two places, latter can be removed. (..... These uncertainties can stem from uncertainties in data).

Action: Done.

Comment 9: Please add some references for sources of uncertainty. For example, in hydrological modelling application, uncertainties are from 1) model input data 2) structural uncertainty 3) parameter uncertainty

Response: We have cited the literature published by Beven and Brazier (2011) and JCGM (2008) on source of uncertainties in the erosion model predictions (Page 2, Line 4). However, research on uncertainties estimation for soil erosion and sediment yield is very few which are mostly covered in the Introduction section (Page 2, Line 20 – Page 3, Line 33).

Comment 10: Page 5: Line 4: sentence not clear “role of uncertainties in input parameters on uncertainties in the estimates”

Action: We have corrected the sentence in the revised manuscript. The modified sentence is “*The Garra River, a Himalayan tributary of River Ganga, was selected for demonstration of the developed methodology and for investigating the role of uncertainties in input parameters and SE and SY estimates*”.

Comment 11: Page 5: Line 1 indicated river as ungauged, but Line 24 suggest one gauging station. Please clarify!

Response: The study basin has two gauging stations where sediment yield is measured - (1) Nanak Sagar Dam at upstream and (2) Husepur at downstream. Validation of modelled results are done by using data from these two gauge stations. However, Line 1 indicates that presented methodology can be applied to an ungauged basin.

Comment 12: Page 6, Line 8: SE is estimated by Revised Universal Soil Loss Equation (RUSLE).....The abbreviation should be used the first time when it is mentioned. RUSLE has been mentioned many time in above sections. Same applies to others also.

Action: Agreed and done.

Comment 13: Page 6: 25. It would be useful to define the SDR with proper reference. Example: SDR is defined as the sediment yield from a catchment area divided by gross erosion of the same area.

Action: We have defined SDR in Page 4 lines 8 – 10 and provided reference for it (Walling, 1983; Richards, 1993; USDA, 1972; De Vente et al., 2007).

Comment 14: Figure 4a: check the legend

Response: Figures 4(a) is a rainfall erosivity map which is derived from average annual rainfall values.

Comment 15: Figure 7 appears before Figure 5 in the text

Action: Corrected.

Comment 16: Page 19: Line 8: inconsistency in references

Action: Checked and corrected.

References:

Beven, K. J., & Brazier, R. E. Dealing with uncertainty in erosion model predictions. *Handbook of Erosion Modelling*, 52-79, 2011.

De Vente, J., Poesen, J., Arabkhedri, M., & Verstraeten, G. The sediment delivery problem revisited. *Progress in Physical Geography*, 31(2), 155-178, 2007.

JCGM. Evaluation of measurement data - Guide to the expression of uncertainty in measurement. Working Group 1 of the Joint Committee for Guides in Metrology (JCGM/WG 1), 2008.

Rajeevan, M., & Bhate, J. A high resolution daily gridded rainfall dataset (1971–2005) for mesoscale meteorological studies. *Current Science*, 96(4), 558-562, 2009.

Richards, K. Sediment delivery and the drainage network. *Channel network hydrology*, 221-254, 1993.

Shepard, D., A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM national conference* (pp. 517-524). ACM, 1968.

USDA. Sediment sources, yields, and delivery ratios. *National Engineering Handbook*, Section 3 Sedimentation, 1972.

Walling, D. E. The sediment delivery problem. *Journal of hydrology*, 65(1), 209-237, 1983.

Dear Dr Panagos,

We sincerely thank you for your valuable comments on this manuscript. We have tried our best to incorporate all your suggestions. Detailed answers to the specific questions are given in the following paragraphs.

Comment 1: In the current study, the erosivity factor (R-factor) has high uncertainties. I am not in favor of functions which estimate erosivity based on annual or monthly rainfall values (you can see the low quality results with large pixels in R-factor). Currently there is an increasing availability of high temporal resolution rainfall data which allow to estimate rainfall erosivity according to the principles of USLE/RUSLE. The recent publication and data availability of Global Rainfall Erosivity has demonstrated this and there are about 250 stations with measured R-factor in India.

Response 1: We agree that R factor estimated using high temporal resolution (sub – hourly) dataset based on the principles of USLE/RUSLE is better than that estimated using coarser resolution (monthly or annual) rainfall values. High-resolution rainfall datasets are available for the recent period (example R factor estimated in Global Rainfall Erosivity dataset for India uses hourly data of 250 rain gauges for 2007 – 2015). However, such high-resolution rainfall datasets are not available for the entire study period that starts from 1962 (selected as per the availability of sediment yield records). Since significant annual and decadal variability in the rainfall pattern exists over India, R factor estimated for the recent period may not be a true representative of the study period ranging from 1962 – 2008. Hence, we used IMD dataset for the study that are available at a spatial resolution of 0.25 degree for 1901 – 2013 based on more than 6,000 rain gauge stations over India. Further, the framework proposed for quantifying and propagating uncertainties in SE, SDR and SY estimates, which is the main focus of this paper, is applicable for R factor derived from different resolution datasets based on different principles.

In this study, we selected equation proposed by Babu et al. (1978) that was developed using the rainfall data from various meteorological stations in India (Eq. a in Table 2 in the manuscript). This equation is based on the linear regression between annual average rainfall amounts and R factor. Originally, this equation was proposed to estimate R factor in meter tonnes cm / ha hr unit which needs a multiplication factor of ‘9.8’ to convert into MJ mm/ ha hr unit (Foster et al., 1981). We had missed this factor in our estimate.

Action: We have incorporated the updated value of R factor and revised the subsequent results. Revised R factor are given in Table 1 and shown in Figure 1(c).

Comment 2: Regarding soil erodibility, the recent developments show that also soil structure and Stoniness should be taken into account. Moreover, an additional source of uncertainty has to do with interpolating methods (how did you produce surface maps from the Kfactor measurements) and the high organic carbon soils (there is literature about how to interpolate K-factor and how to face the issue of high soil organic carbon).

Response 2: The present study accounts for soil structure in K factor estimates by using soil structure classification (sc) given by Wischmeier and Smith (1978). The equation (c) in Table 2 provides the equation for K factor estimate, and the structure classification codes are given in the annotation (page 15, line 23).

The Garra basin has primarily three kinds of soil textures: loam, sand and sandy loam (Figure 2c) with negligible amount of gravels. Hence, stoniness is not accounted in the K factor estimates. We will explicitly mention this fact in the revised manuscript.

Soil in the Garra basin has organic matter (OM) less than 0.2%. This value is much smaller than 4%, the maximum range of OM for which Wischmeier and Smith (1978) equation for K factor estimate is applicable.

The K factor is obtained based on NRSC (National Remote Sensing Center) soil dataset available at a spatial resolution of 56m. Thus, no interpolation is performed in estimating K factor map. Instead, the interpolation was performed by NRSC in preparing the soil data. Since NRSC did not provide the interpolation uncertainty, it was not included in the study.

Action: This limitation arising due to non-availability of interpolation error in soil data (also present in rainfall and LULC data) will be mentioned in section 5 (Limitations) of the revised manuscript.

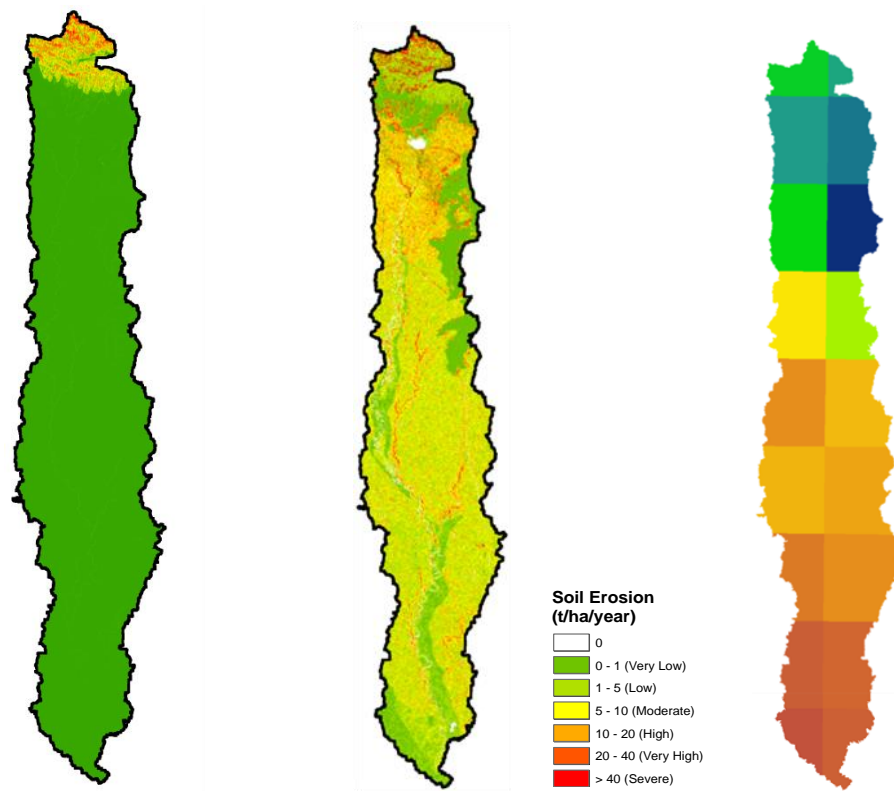
Comment 3: In the topographic factor, authors do not discuss the pixel size issue. There much higher uncertainty when LS-factor is calculated with pixels of 90m resolution compared too much higher resolution of 25m (all this has been discussed in European application of LS-factor). Moreover, I see values of LS-factor = 2465 .This is impossible for soil coverages.

Response 3: In the literature review section, we have given references that discuss the issue of LS factor uncertainty due to cell size variation (page no. 2, line 25). However, this issue was not discussed in length because the objective of this paper is not to study the effect of cell size variation on LS factor uncertainty, but rather to provide a methodology to estimate LS factor uncertainty arising due to errors in DEM (geo-location and elevation errors). Different resolution DEMs obtained from different measurement techniques (remote sensing or ground based survey) may have different geo-location and elevation errors resulting in different LS factor uncertainties. The proposed methodology can be used to estimate LS factor uncertainty irrespective of the DEM resolution or measurement techniques used for its preparation.

Yes, LS factor cannot be so high. It was a plotting error which has been corrected. Furhter, we have improved the value of slope length exponent (m). In the previous version, the exponent is estaimted assuming rill to interrill ratio (β) as 0.67. In the revised version, β is estaimted based on basin median slope (Morgan, 2016; McCool et al., 1997), which changed m from 0.40 to 0.14. The resulting LS factor is shown in Fig 1(a) below and its range is given in Table 1.

Table 1 compares the earlier and revised estaimtes of R and LS factors, and soil erosion. Table 2 presents the revised estaimtes of sediment yield at Nanak sagar dam (NSD) and Husepur gauging station (HSG). Compared to the earlier estimates, the revised estimates are closer to observed sediment yield at both the locations.

Action: We have changed the Figure 4 (c) and updated LS factor values.



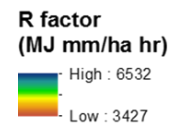
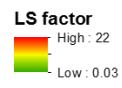


Figure 2 (a) Modified LS factor (b) re-classified soil erosion map (c) Modified R factor

Comment 4: The cover management factor is the most uncertain in USLE applications. In the manuscript it is not clear (Table 3c) how you got those C-factor ranges and how you calibrate at pixel level? The use of remote sensing on vegetation density may help you on this.

Response 4: Yes, we agree that the cover management (CP) factor is the most uncertain among other
5 RUSLE factors. This is evident in our results shown in Fig 6(c), where the magnitude of CP factor
uncertainty is much higher than other factors.

The C factor ranges given in Table 3 are obtained from Morgan (2009; table 6.2, page no. 122). The ranges
for different LULC classes were used to estimate uncertainty in C factor by assuming a triangular
distribution that spans the entire range of C factor (equation (i) in table 2).

10 The vegetation density obtained using remote sensing (vegetation indices) can provide an alternative method
to quantify C factor and its uncertainty.

Action: This have been included in the revised manuscript (Page 2 Line 16 – 17).

Comment 5: Also how did you find the P-factor values? The literature has quite different values.

Response 5: The P factor is obtained from Morgan (2009; table 6.3, page no. 123). The table provides P
15 factors for contour and strip cropping based on slope conditions.

**Comment 6: (a) The first concluding remark is not valid. this is obvious! (b) The soil erosion map
could have at least 6-7 classes to show a clear distinction between low erosion , low medium , medium,
high , severe, etc (with colours from Green to Red). (c) Tables should be self-explained. I don't agree
with the current structure presenting the equations in the table and having the factors and annotations
20 in separate page. It is not easy for readers.**

Response 6:

- a) The point is not a concluding remark, but it summarises the work done. We will remove this point
from the revised manuscript.
- 25 b) Figure 1(b) in this response shows the soil erosion map with six classes (increased from four in the
original manuscript). We hope that the new figure distinguishes different soil erosion areas.
- c) Thanks for the suggestion. In the revised manuscript, symbols will be explained along with the
equations in which they are used.

Table 3 Earlier and modified R, LS and soil erosion values

Factor	R factor (MJ mm/ha hr year)		LS factor		Soil Erosion (t/ha/year)	
	Earlier	Now	Earlier	Now	Earlier	Now
Minimum	666.5	6532	0.09	0.03	0	0
Maximum	349.7	3427	53	22	1356	1423
Mean	467.3	4579.5	5.4	0.6	20.4	23

Table 4 Earlier and modified sediment yield values

Station	Observed	Earlier	Now
Nanak Sagar	6.4×10^5	8×10^5	6.9×10^5
Husepur	7.2×10^6	7.9×10^6	6.7×10^6

5

References:

Babu, R., Tejawani, K. G., Agarwal, M. C., & Bhushan, L. S. Distribution of erosion index and iso-erodent map of Inia. Indian Journal of Soil Conservation, 1978.

10 Foster, G. R., McCool, D. K., Renard, K. G., & Moldenhauer, W. C. Conversion of the universal soil loss equation to SI metric units. Journal of Soil and Water Conservation, 36(6), 355-359, 1981.

McCool, D.K., Foster, G.R. & Weesies, G.S. Slope length and steepness factors. In Renard, K.G., Foster, G.R., Weesies, G.A., et al. (eds), Predicting soil erosion by water: a guide to conservation plan- ning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agricultural Handbook 703, 1997.

Morgan, R. P. C. Soil erosion and conservation. John Wiley & Sons, 2009.

15 Morgan, R. P. C., & Nearing, M. (Eds.). Handbook of erosion modelling. John Wiley & Sons, 2016.

Wischmeier, W. H., & Smith, D. D. Predicting rainfall erosion losses. Agricultural Handbook no. 537, US Department of Agriculture. Science and Education Administration, 1978.

Assessment of uncertainties in soil erosion and sediment yield estimates at ungauged basins: an application to the Garra River basin, India

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Abstract. High soil erosion and excessive sediment load are serious problems in several Himalayan River basins. To apply mitigation procedures, precise estimation of soil erosion and sediment yield with associated uncertainties are needed. Here, Revised Universal Soil Loss Equation (RUSLE) and Sediment Delivery Ratio (SDR) equations are used to estimate the spatial pattern of soil erosion (SE) and sediment yield (SY) in the Garra River basin, a small Himalayan tributary of River Ganga. A methodology is proposed for quantifying and propagating uncertainties in SE, SDR and SY estimates. Expressions for uncertainty propagation are derived by first-order uncertainty analysis, making the method viable even for large river basins. The methodology is applied to investigate the relative importance of different RUSLE factors in estimating the magnitude and uncertainties of SE over two distinct morpho-climatic regimes of the Garra River basin, namely, upper mountainous region & lower alluvial plains. Our results suggest that average SE in the basin is very high (23 ± 4.7 t/ha/y) with higher values in the upper mountainous region (92 ± 15.2 t/ha/y) compared to the lower alluvial plains (19.3 ± 4 t/ha/y). Furthermore, the topographic steepness (LS) and crop practice (CP) factors exhibit higher uncertainties than other RUSLE factors. The annual average SY is estimated at two locations in the basin - Nanak Sagar dam (NSD) for the period 1962-2008 and Husepur gauging station (HGS) for 1987-2002. The SY at NSD and HGS are estimated to be $6.9 \pm 1.2 \times 10^5$ t/y and $6.7 \pm 1.4 \times 10^6$ t/y, respectively, and the estimated 90% interval contains the observed values of 6.4×10^5 t/y and 7.2×10^6 t/y respectively. The study demonstrated the usefulness of the proposed methodology for quantifying uncertainty in SE and SY estimates at ungauged basins.

1. Introduction

Soil erosion is a serious problem, which not only causes land degradation and loss of agricultural productivity but also alters geomorphic processes and sediment fluxes in a river basin. Estimation of soil erosion (SE) and sediment yield (SY) of a river basin are therefore essential for agricultural planning and river management. SE and SY can be estimated by either empirical models that are developed solely based on experimental studies (e.g. USLE, RUSLE and MUSLE) or process-based models that are based on parameterization of physical processes e.g. Water Erosion

Prediction Project (WEPP), Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) and Agricultural Nonpoint Source (AGNPS). While the process-based models may be more reliable and appealing, the empirical models are popular because they can be applied on basins with no or limited data (Merritt et al., 2003).

The estimates of SE and SY alone are not sufficient for effectively addressing soil erosion problem in a river basin. One needs to quantify uncertainties in those estimates as well. These uncertainties can stem from input data (measurement errors, coarse spatial and temporal resolution, missing values), model (parameter, structural, and algorithmic or numerical uncertainty), and stochastic nature of the soil erosion process (Beven and Brazier, 2011; JCGM, 2008). Since quantification of all the sources of uncertainties is difficult, studies make assumptions about their relative importance and mutual independence. Nevertheless, to the best of authors' knowledge, no unified approach is available to quantify uncertainty in SE and SY estimates for ungauged basins. The following paragraphs briefly review the literature on the uncertainty estimates of SE and SY and highlight the existing gaps.

Arguably, the most popular empirical model for estimating SE is USLE and its variants such as RUSLE and MUSLE. Variations of USLE are also used in distributed hydrological models like Evaluation of the Water Quality Model (EUTROMOD), Soil and Water Assessment Tool (SWAT) and Simulator for Water Resources in Rural Basins (SWRRB). The USLE estimates sheet and rill erosion but does not account for gully or channel erosion in a basin. Developed in 1960s with more than 10,000 plot-yr data from USA, the method was designed for estimating long-term SE at a plot-scale, but it is now frequently used for estimating erosion at a basin-scale, albeit with some modifications. This study uses RUSLE model that estimates SE by considering five factors, namely, rainfall and runoff erosivity (R factor), soil erodibility (K factor), topography (LS factor), cover and management (C factor) and support practice (P factor).

The studies on uncertainty analysis of RUSLE equation can be divided into three groups:

- (a) Studies that have quantified uncertainties in individual factors of the RUSLE equation. For example, Wang et al. (2002b) quantified spatial uncertainty in R factor by using geostatistics. Catari et al. (2011) assessed uncertainty in R factor by comparing traditional methods with at-site measurements. Torri et al. (1997), Wang et al. (2001) and Parysow et al. (2003) investigated uncertainty in K factor by using geostatistical methods. Gertner et al. (2002), Wang et al. (2002a), Wu et al. (2005) and Mondal et al. (2016) estimated uncertainty in LS factor based on at-site measurements and cell variation in digital elevation model (DEM).
- (b) Studies that have used backward or inverse uncertainty propagation in which modeled and observed values of SE are compared to evaluate model biases, check model's suitability for a basin, and estimate model parameters (Risse et al., 1993; Falk et al., 2010 and Carmona et al., 2017). The backward uncertainty analysis requires observed values of SE, and hence not applicable for ungauged basins.

(c) Studies that have used forward uncertainty propagation in which uncertainties present in input data and/or model are propagated to quantify uncertainties in the SE estimates. A few studies (Hession et al., 1996; Biesemans et al., 2000; Tetzlaff and Wendland, 2012); Tetzlaff et al., 2013) that are relevant for this work are summarized below.

5 Hession et al. (1996) presented a two-phase Monte Carlo methodology for forward propagation of uncertainty and demonstrated its application at an experiential plot in Oklahoma, USA. They divided uncertainty in USLE factors into knowledge uncertainty and natural stochastic variability and argued that the two types of uncertainties should be analyzed separately to draw useful conclusions. They considered knowledge uncertainty for R factor, stochastic variability for K and C factors, and treated LS and P factors as constants. They also studied the effect of spatial discretization in models and the assumption of independence of parameters on uncertainty quantification. However, 10 since information on dependence of USLE factors was not available, they assumed different levels of correlation among them.

Biesemans et al. (2000) applied Monte Carlo error propagation technique for estimating uncertainty in SE and SY (referred to as off-site sediment accumulation) at a watershed in Belgium. Elevation data were assumed to have auto-correlated errors, which were modeled using fractional Gaussian noise to estimate uncertainty in LS factor. Soil texture and its organic content were measured at 153 locations in the watershed to estimate K factor. The K factors so obtained were interpolated using Kriging. The variance of the Kriging surface was taken as a measure of K factor uncertainty. The C factor was assumed to have uniform distribution with minimum and maximum values estimated based on USLE table and by appropriately weighing C factor for each crop by the erosivity value in its growing season. R and P factors were assumed constant. The result showed that the observed value of SE lies within one standard error of the estimated 15 mean value, prompting authors to conclude that RUSLE is a suitable model for their study watershed and that the RUSLE model should use probability distribution of input factors rather than their fixed values. 20

Tetzlaff and Wendland (2012) and Tetzlaff et al. (2013) performed forward uncertainty analysis on ABAG model (an adaptation of USLE to German conditions) by using Gaussian error propagation and Monte Carlo simulations. ABAG was a part of MEPhos model that was applied to determine SY for the state of Hesse in Germany (21,115 km²). 25 However, because of high computational cost, the uncertainty analysis for SE using ABAG was performed for a relative small catchment of River Gersprenz (485 km²). The uncertainty in LS factor was estimated as standard deviation of 1,000 LS factors derived from 1,000 simulated DEM surfaces obtained by adding random Gaussian error to the original DEM. Uncertainties for the other USLE factors were assumed (R- 10%, C – 23%, and K-10%) based on auxiliary information, and P factor was treated as constant. The authors calculated that the uncertainty in USLE factors resulted 30 in 34% uncertainty in the mean annual soil loss estimates.

Not all of the sediment eroded in a basin is delivered out of it; a significant portion of the eroded material gets deposited at intermediate locations. Sediment yield (SY) denotes the total sediment outflow from a basin over a specified duration. It is usually measured by either stream flow sediment sampling or reservoir sedimentation survey. By definition, SY includes both bed load and suspended load. However, since streamflow sediment sampling is often restricted to suspended load, the SY estimates from streamflow sampling are usually adjusted upward by some empirical procedure (e.g. Table 3.2 of Vanoni, 1975).

Reviews on SY modeling suggest that unlike SE modeling, no universal relationships are available that can be applied to every situation, rather region-specific relationship is considered to be the best method for predicting SY (Ludwig and Probst, 1998; De Vente et al., 2011). The most common approach to predict SY is to estimate it as a product of gross SE and sediment delivery ratio (SDR; Walling, 1983; Richards, 1993), where SDR is defined as the ratio of SY at a prediction location to the gross or total SE of a basin whose outlet is the prediction location. Precise estimate of SDR is not available, but it is primarily related to the drainage basin area (USDA, 1972; De Vente et al., 2007). According to Boyce (1975), SDR generally decreases with increasing basin area because with increase in basin size mean slope decreases and sediment storage locations between source areas & the basin outlet increases. The most favored method for long-term SY estimation is USLE-SDR method where gross SE is estimated by the USLE model (e.g., Ebisemiju, 1990; Walling, 1993; Van et al., 2001; Amore et al., 2004; Bhattarai and Dutta, 2007; Boomer et al., 2008). This study uses RUSLE-SDR model for predicting SY, in which SDR is obtained as a function of basin area based on the equation developed for north Indian River basins by Sharda and Ojasvi (2016).

Only a few studies have reported uncertainty in SY estimates by using USLE-SDR approach. Ferro & Porto (2000) and Stefano & Ferro (2007) quantified uncertainty in the estimates of SY for river basins in Italy using a USLE-SDR based model termed sediment delivery distributed (SEDD) model. The model could predict SY at event and annual scales, but requires observed data for its calibration and hence not suitable for ungauged basins. Catari (2010) used RUSLE-SDR model to investigate uncertainty in the estimates of SY for the Upper Llobregat River basin in Spain. The uncertainties in individual RUSLE factors and SDR are first quantified and then added in quadrature to estimate uncertainty in SY. The LS and C factors were found to have the major influence on SY uncertainty.

The literature review on SE and SY estimation described in the foregoing paragraphs suggest that – (i) Very few studies have computed uncertainties in SE and SY for ungauged basins. Most of the existing studies are either restricted to plot-scale or are carried out for basins with measured data; (ii) While the importance of sediment erosion in Himalyan basins is well known (Galy and France-Lanord, 2001; Rahaman et al. 2009), no studies are available that have quantified uncertainties in SE and SY estimates for these basins; (iii) Presence of storage structures, like dams and reservoirs, complicates the estimation of SY downstream of the structure. Though some simplified methods exist to account for

control structures in SY estimation (Sharda and Ojasvi, 2016), their effects on the uncertainty quantification have not been explored.

The aim of this study is to develop a methodology for determining uncertainties in SE and SY estimates of ungauged basins. The Garra River, a Himalayan tributary of River Ganga, was selected for demonstration of the developed methodology and for investigating the role of uncertainties in input parameters and SE and SY estimates. The specific objectives of this study are:

- (i) To estimate spatially distributed SE for the Garra River basin using the RUSLE model.
- (ii) To quantify uncertainty in SE estimate by accounting for uncertainties in different RUSLE factors.
- (iii) To study the relative importance of different RUSLE factors in governing erosion and its uncertainty over mountainous and alluvial plain regions of the basin.
- (iv) To estimate SDR and its uncertainty for the Garra River basin.
- (v) To evaluate SY and its uncertainty for the basin by combining SE and SDR estimates.

Remainder of the paper is organized into four sections. Section 2 describes the study area and data used. Section 3 presents the methodology for estimating SE, SDR and SY, and for quantifying uncertainties in these estimates. Section 4 describes the results obtained, and Section 5 lists the limitations of the proposed methodology. Finally, Section 6 summarizes the major finding of this work and presents a set of concluding remarks.

2. Study Area & Data Used

The study basin is the Garra/Deoha River, a Himalayan tributary of River Ganga. This river originates near Haldwani in Uttarakhand from a lake (29°12'16" N, 79°45' 30" E) fed by glacier melt (Roy and Sinha, 2007), and meets River Ganga near Kannauj in Uttar Pradesh (27°08'30" N, 79°56'40" E). The study basin is located between 27°09' N to 29°18' N latitude and 79°38' E to 80°09' E longitude, covering a total area of around 7,000 km² (Fig. 1). The Garra basin has two distinct morpho-climatic regimes, upper mountainous region (part of Himalayan foothill) and lower alluvial plains (part of upper Indo-Gangetic plains). The upper mountainous region of the basin has a high average annual rainfall of 1,500 mm, and the lower alluvial part has a comparatively lower average annual rainfall of 1,050 mm (Fig. 2d).

The only gauging station in the basin is at Husepur (27°16'30" N, 79°57'0.64" E) near Hardoi, Uttar Pradesh, which was operated by the Central Water Commission (CWC) from 1987-2002. The discharge and suspended sediment load records for 16 years (1987 – 2002) are available at this station. Topography, land use land cover (LULC), soil and rainfall datasets are obtained from different data source agencies listed in Table 1. Table 1 also provides the spatial and temporal resolutions, and temporal extent of these datasets.

The Garra River has a major intervention in the form of Nanak Sagar reservoir (28°57' 10" N, 79°50'30" E; capacity 210 Mm³) created by a dam of the same name built in 1962. The reservoir's average sedimentation rate data for the period 1962 – 2008 (47 years) measured by storage capacity survey are available from a report (CWC, 2015).

3. Methodology

This section describes the methods used for computing SE & SY, and their associated uncertainties. Following the guidelines given by the Joint Committee for Guides in Meteorology (JCGM, 2008), the uncertainties are expressed using standard deviation and reported as percentage of the mean value (Coefficient of Variation, CV). To combine uncertainties, the general principle of adding uncertainties in quadrature is used (Taylor, 1982). The principle assumes that the individual uncertainties are independent.

3.1 Estimation of Soil Erosion (SE)

SE is estimated by Revised Universal Soil Loss Equation (RUSLE), which is an empirical model for predicting long-term average rate of SE based on crop system, management techniques, and erosion control practices (Renard et al., 1991; Kinnell, 2008). The SE is expressed as a function of five input factors (Eq. 1): rainfall and runoff erosivity (R), soil erodibility (K), slope length and steepness (L & S), cover management (C) and support practice (P) (see Table 2 for their units). These input factors vary considerably from storm to storm, but their effects on the estimation of SE tend to be averaged over extended periods (Wischmeier and Smith, 1978). The methodology for determining the input factors and their uncertainties at each evaluation cell is described below.

$$SE = R K L S C P \quad (1)$$

3.1.1 Rainfall and Runoff Erosivity Factor (R)

The R factor quantifies the raindrop impact and gives information about the amount and rate of runoff likely to be associated with the rain. The R factor can be obtained by estimating rainfall kinetic energy from rainfall intensity data (Wischmeier and Smith, 1978). As rainfall intensity data are not easily available, empirical equations have been proposed to calculate R factor from the readily available average annual rainfall data (denoted by r). In this study, we selected the equation proposed by Babu et al. (1978) using the rainfall data from various meteorological stations in India (Eq. a in Table 2). Originally, this equation was proposed in ‘meter tones cm / ha hr year’ unit by Babu et al. (1978), which needs a multiplication factor of ‘9.8’ to convert into ‘MJ mm/ ha hr year’ unit (Foster et al., 1981). The uncertainty in the estimate of R factor arises from model error in the Babu et al.’s equation and variability in observed average annual rainfall (δr). Since model error for Babu et al.’s equation is not available, the uncertainty in R (δR) is estimated solely based on observed rainfall variability (Eq. b, Table 2).

3.1.2 Soil Erodibility Factor (K)

This factor represents the susceptibility of soil to erosion due to rainfall and runoff. The K factor is usually obtained from one of the many empirical equations (Wischmeier and Smith, 1978; Declercq and Poesen, 1991; Van der Knijff et al., 2000) that relate it to soil properties like organic matter percentage, soil texture, and soil permeability. **However, stoniness can also be an important factor to consider while evaluating K factor (Panagos et al., 2014).** The Garra basin has primarily three kinds of soil textures: loam, sand and sandy loam (Figure 2c) with negligible amount of gravels. Hence, stoniness is not accounted for in the estimates of K factor. Therefore, the equation proposed by Wischmeier and Smith (1978) (Eq. c, Table 2) is used for estimating the K factor because all the required input parameters for this equation are available for the study basin. The uncertainty in the K factor can be due to uncertainty in the measurement of soil properties and uncertainty in the model that relates soil properties to K factor. Since the measurement uncertainties for soil properties are not available for the study basin, only the model uncertainties as given by Wischmeier and Smith (1978) are considered (Table 2).

3.1.3 Slope-Length factor (L) & Slope Steepness factor (S)

The L & S factors represent the effect of topography on SE. They are usually presented as a single factor (LS factor) that represents the ratio of soil erosion for the given conditions to the soil erosion from an experimental plot of slope length 22.13 m and slope steepness 9%. This study employs the method proposed by Desmet and Govers (1996) for determining the L factor (Eq. d in Table 2). The method calculates the L factor by considering flow accumulation at each cell obtained from DEM. The S factor depends only on the local slope. Many empirical equations are available for estimating the S factor (Wischmeier and Smith, 1978; McCool et al., 1987; Moore and Wilson, 1992; Nearing, 1997). Here, the equation proposed by McCool et al. (1987) is adopted because of its popularity and versatility (Eq. f in Table 2).

Monte Carlo simulations are usually employed for quantifying uncertainties in LS factor (Biesemans et al, 2000; Catari, 2010; and Tetzlaff et al., 2013). In this method, multiple realizations of DEM are generated based on pre-specified error rate in DEM elevation, and LS factor is calculated for every realization. The variability in LS factors over multiple realizations provides a measure of uncertainty in the LS factor arising due to uncertainties in DEM. The DEM errors are sometimes modeled as an auto-correlated random field (Biesemans et al, 2000); however, in absence of information about the spatial structure of the DEM errors, they are either modeled as independent errors (Tetzlaff et al., 2013) or some simplified assumptions are made on their spatial structure using spatial filters (Catari, 2010). The assumption of independent errors gives the worst-case scenario of DEM uncertainty effects (Wechsler and Kroll, 2006). The Monte Carlo simulations are effective for small sized basins, but become tedious for large basins (Tetzlaff and Wendland, 2012). This study uses the information on geo-location error ($\delta\Delta x$) and elevation error ($\delta\Delta h$) available for the DEM,

and applies first-order uncertainty analysis to estimate uncertainties in L (δL) and S (δS) factors (Eqs. e and g in Table 2). The method assumes that the DEM errors are uniform in space and are independent.

The uncertainty in L factor also depends on the uncertainty in specifying the value of variable slope exponent (m). The m factor depends on rill and interrill erosion ratio (β). In this study, β is estimated by the equation proposed by McCool et al. (1997). Here, the uncertainty in ' m ' is modeled as a Type B standard uncertainty assuming symmetric triangular distribution (JCGM, 2008, pages 11 to 18) over the range of value (0.05 – 0.25). The combined uncertainty in LS factor (δLS) is obtained by adding δL and δS in quadrature.

3.1.4 Cover and Management (C) & Support Practice Factor (P)

The C factor is the ratio of soil loss from a given land use class to the corresponding loss from an experimental plot having “clean-tilled and continuous fallow” land use condition. The P-factor is the ratio of soil loss from a land with given support practice to the corresponding loss from an experimental plot having an agricultural practice of “upslope and downslope tillage.” The C and P factors for a cell are obtained from reference tables (Morgan, 2009; FAO, 1978) that provide a range for given land use and agricultural practices. Reference values of C & P factors for the classes of land use and agricultural practices considered in this study are given in Tables 3 & 4, respectively. Since RUSLE model is not applicable for glacial erosion and channel processes, the C factor for snow and water covered cells is taken as zero. The vegetation density obtained using remote sensing (Normalized Difference Vegetation Index) can provide an alternative method to quantify C factor and its uncertainty.

For an agriculturally dominated basin, the C factor varies seasonally depending upon the cropping cycle. The seasonality in C factor is incorporated in RUSLE by taking a weighted average of C values during different seasons, where weights are proportional to the R factor (Vanoni, 1975). The study basin has two types of cropping patterns - (1) double & triple cropping pattern in which crops are grown almost all year round, and (2) single cropping (Rabi/ Kharif/ Zaid) system in which the crops are grown only for a season. Since the farms with single cropping pattern are fallow during the non-growing season they are attributed with a wider range of C factor (0.3 – 1) compared to the farms with double & triple cropping pattern (0.3 – 0.5).

During field visits, we observed that terrace cropping and strip cropping are practiced in most of the upper mountainous region and lower alluvial plains, respectively. For calculating SE, it is assumed that the upper mountainous region has only terrace cropping practice and lower alluvial plains have only strip cropping practices. The uncertainty in C (δC) and P (δP) factors are obtained by Type B evaluation of standard uncertainty, assuming symmetric triangular distribution over the range of values in a given class of land use and agricultural practice (JCGM, 2008), presented in Table 2 (Eqs. i & j). The combined effect of land use and land cover is represented by the CP factor, which is a product of C and P factors. The uncertainty in CP factor (δCP) is calculated by adding δC and δP in quadrature.

Finally, assuming that uncertainties in individual factors are independent, they are added in quadrature to calculate relative uncertainty in the estimate of SE for each cell as –

$$\frac{\delta SE}{SE} = \sqrt{\left(\frac{\delta R}{R}\right)^2 + \left(\frac{\delta K}{K}\right)^2 + \left(\frac{\delta LS}{LS}\right)^2 + \left(\frac{\delta CP}{CP}\right)^2} \quad (2)$$

3.2 Estimation of Sediment Delivery Ratio (SDR)

- 5 The SDR is defined as the ratio of SY at a prediction location to the gross or total SE of a basin. It is estimated by the empirical equation developed by Sharda and Ojasvi (2016) based on reservoir sedimentation (CWC, 2015) and soil erosion data (Sharda, 2009; NAAS, 2010) from sixteen large reservoir basins (basin area greater than 1,000 km²) located in north India (Eq. 3).

$$SDR = 1.817 \times A^{-0.132} \quad (3)$$

- 10 For derivation of the above equation, soil erosion rates for India were estimated by employing RUSLE equation, but with inconsistent unit system for R and K factors (Maji, 2007; NAAS, 2010). After applying the correction, the SDR values decreases by a factor of 1.28. The corrected equation is

$$SDR = 1.42 \times A^{-0.132} \quad (4)$$

- 15 The equation was fitted by the ordinary least squares method in the logarithmic domain. An expression for uncertainty in SDR prediction (δSDR) that accounts for model error ($\delta SDR_{\text{model}}$) and uncertainty in the calculation of basin area ($\delta SDR_{\text{input data}}$) derived by using the first-order uncertainty analysis is given by Eq. n in Table 2.

3.3 Computation of Sediment Yield (SY)

- 20 The SY at a location is estimated by multiplying annual average gross SE and SDR of a drainage basin whose outlet is the estimation point. The uncertainty in SY is computed as the standard deviation of the SY distribution obtained by 1000 Monte Carlo simulations for which gross SE and SDR are simulated using the following distributions:

- (i) The gross SE is the sum of average annual SE at all cells in the basin. Assuming weak form of central limit theorem to be applicable (i.e. probability distribution of annual average SE at all cells in the basin are non-independent and non-identical), the gross erosion is considered to have a normal distribution with mean and variance equal to sum of means and variances of SE at individual cells, respectively. A truncated version of the normal distribution in the range $[0, \infty)$ is used to avoid negative values of gross SE during Monte Carlo simulations.
- 25

- (ii) The SDR of the basin is assumed to follow lognormal distribution with mean and standard deviation given by Eqs. (k) and (n) in Table 2, respectively.

In addition to Monte Carlo simulations, uncertainty in SY is also estimated by the first-order uncertainty analysis.

To account for the effect of a dam on SY, we used the method proposed by Sharda and Ojasvi (2016) which assumes that a sufficiently large dam on a river (termed terminal dam) entraps all the sediment carried by the river into its reservoir. Therefore, the gross SE at a location downstream of a terminal dam is estimated from "free basin area" (total basin area – reservoir catchment area) instead of total basin area. The SY is then calculated as the product of gross SE from the free basin area and SDR of the entire basin.

In this study, annual average SY is estimated at two locations – Nanak Sagar dam for the period 1962-2008 and Husepur gauging station for the period 1987-2002. The Nanak Sagar dam, which lies upstream of the Husepur station, is treated as a terminal dam.

The following steps are followed to estimate the values and corresponding uncertainties of SE, SDR and SY (also shown as a flow chart in Fig. 3):

- (i) The Garra River basin boundary is derived from SRTM data based on D8 flow direction algorithm (O'Callaghan and Mark, 1984). Hydrological correction of DEM is done by filling of pits in topography (Tarboton et al., 1991). Flow accumulation, flow direction, drainage network and local slope are calculated from the corrected DEM of the Garra River basin.
- (ii) The R, K, L, S, C & P factors and their uncertainties are calculated by using the equations given in Table 2 and explained in the previous sections.
- (iii) Spatially distributed SE averaged over the study period is estimated by applying RUSLE equation. The uncertainties in individual factors of RUSLE are propagated by first-order uncertainty analysis (Table 2 and Eq. 2) to calculate uncertainty in the estimated SE at each cell. Monte Carlo simulations are used to predict the distribution of SE.
- (iv) Mean and variance of gross SE for a basin is estimated by summing up mean and variance of SE at all cells in the basin.
- (v) SDR for a basin is modeled as a lognormal distribution with mean and standard deviation estimated from Eqs. (k) and (n) in Table 2, respectively.
- (vi) SY at the Nanak Sagar dam (NSD) and Husepur gauging station (HGS) are estimated by Monte Carlo simulations. 1,000 values of gross SE (normal distribution) and SDR (lognormal distribution) are generated and multiplied with each other to simulate 1,000 values of SY. The uncertainty of SY prediction interval is reported as the standard deviation of the simulated SY values.

(vii) The estimated annual average SY at NSD (1962-2008) and HGS (1987-2002) are compared with observed values to assess the suitability of the proposed methodology.

4. Results and discussion

4.1 Soil erosion (SE)

5 First, the results of RUSLE factors are presented, which are followed by the results of SE estimation. The results presented are the average value during the entire study period (1962 – 2008).

4.1.1 R factor

10 The R factor (Fig. 4a) follows the same spatial pattern as average annual rainfall (Fig. 2d) - high in the upper mountainous region where average annual rainfall exceeds 1,000 mm. The factor gradually reduces in the lower alluvial parts and attains the minimum values near the basin outlet. The uncertainty in R factor that stems from variability in annual rainfall varies in a relatively narrow range of 3.4% to 6.7% (Fig. 5a).

4.1.2 K factor

15 The soil map (Fig. 2c) shows the presence of sand and sandy loam soil close to the main channel and in forested patches of the basin; the rest of the basin is covered primarily with loam. Typically, the loam is more susceptible to erosion than sand and sandy loam, which is reflected in higher values of K factor (Fig. 4b). The upper mountainous region shows highest values of K factor because the loam in this region has higher silt content (~ 40%) compared to loam in lower alluvial plains (~ 30%). The magnitude of model uncertainty in δK is constant for the basin, hence, the percentage uncertainty is lower for cells with larger K factor (upper mountainous region) than for cells along the main channel that have low value of K factor. The uncertainty varies from 5.4% to 9.6% (Fig. 5b).

20 4.1.3 LS factor

25 The LS factor shows considerable variation, particularly in the upper mountainous region where its value ranges from 5 to 22.3 (Fig. 4c). The larger values and higher variation in the upper mountainous region can be attributed to the steeper slopes (S factor) and its varying topography. The LS factor is also relatively high for cells close to the stream mainly because of the large contributing area (L factor). For the rest of the basin, the LS factor is small (< 1) and shows little variability. The uncertainty in LS factor also shows a considerable variation. The magnitude of uncertainty is significant for cells near the channel and upper mountainous region. However, these cells have least percentage uncertainty ($< 2\%$) because of higher magnitude of LS factor (Fig. 5c). The percentage uncertainty in the rest of the basin varies between 2% and 12% (Fig. 5c).

4.1.4 CP factor

The spatial map of CP factor (Fig. 4d) resembles distinct land use and land cover (LULC) features present in the basin. The factor is zero for snow and water covered cells. It attains a low value (< 0.1) for forested cells (16% of basin area), intermediate values (0.2 – 0.3) for urban cells (0.4% of basin area), and highest values (> 0.4) for cropland cells (71% of basin area). The uncertainty in CP factor also varies according to LULC type and crop practice class as shown in Tables 3 & 4. The percentage uncertainty varies from 8.2% to 13.6% (Fig. 5d).

4.1.5 Soil erosion (SE)

Finally, results of all the factors described in the preceding subsection are combined by using Eqs. (1) and (2) to obtain SE map (Fig. 4e) and its uncertainty (5e), respectively. Two distinct geomorphic settings in the basin – the upper mountainous region and the lower alluvial plains – show significant differences in SE. The factors governing the rate of SE in these two settings are compared in Figs. 6 & 7. The SE is the highest in the upper mountainous region ($SE > 40$ t/ha/y; severe category). For the cells near the channels the rate of erosion falls in the zone of very high (20 to 40 t/ha/y) and severe (> 40 t/ha/y) category. Other parts of the basin have moderate (< 10 t/ha/y) to high (10 – 20 t/ha/y) SE rate. The average rate of SE for the entire Garra basin is 23 t/ha/y (very high), whereas for upper mountainous region and lower alluvial plains the value are 92 t/ha/y (severe) and 19.3 t/ha/y (high), respectively.

The upper mountainous region has higher values of R, K and LS factors than the lower alluvial plains. A significant portion of the alluvial plains has cultivated land where the agricultural practices tend to make the soil more susceptible to sheet erosion during rainfall. Hence, the CP factor is higher for the alluvial plains. Nevertheless, the higher erosion rates in the mountainous region can be attributed mainly to the higher values of LS factor due to steeper slopes.

The uncertainty map of SE rate (Fig 5) reflects the spatial distribution of uncertainty in individual factors. The uncertainty tends to be high for sandy loam and sandy soil patches in the basin. The percentage uncertainty in upper mountainous region is lower (16.5%) than that for the alluvial plains (20.5%). However, uncertainties in the magnitude of erosion rate are higher for mountainous region (15.2 t/ha/y) than for the alluvial plains (4 t/ha/y). The magnitude and percentage uncertainty of RUSLE factors and SE rate averaged over the entire basin is very similar to that of the alluvial plains that constitute a major portion of the basin (95%; Fig. 6b).

Figure 6a shows the distribution of SE at two representative cells in the upper mountainous region and lower alluvial plains obtained by the Monte Carlo simulations. The cell in the mountainous region has higher value of SE and its distribution has wider spread compared to that of the cell in the alluvial plains. Both the distributions are positively skewed, although the magnitude of coefficient of skewness is small (0.11 for mountainous regions and 0.13 for alluvial plains). Table 5 compares the uncertainties in RUSLE factors and SE reported in the literature, and those obtained in the

present study. The reported uncertainties in SE have a wide range that encompasses the uncertainty range estimated in the present study. The backward uncertainty propagation method uses observed data and thus represents true uncertainty. The forward method gives an approximation of the true uncertainty, and usually under predicts the true value.

5 4.2 Sediment Delivery Ratio (SDR) and Sediment Yield (SY)

The SDR and its uncertainty (reported as coefficient of variation in parenthesis) for Nanak Sagar dam (NSD) and Husepur gauging station (HSG) are 0.63 (4.40%) and 0.45 (4.81%), respectively. For both the locations, the SDR model uncertainty component ($\delta SDR_{\text{model}}$) dominates total SDR uncertainty ($\delta SDR_{\text{model}} > 0.95 \delta SDR$). The gross SE at the NSD and HSG sites and its uncertainty are 10.9×10^5 t/y (16.63%) and 14.9×10^6 t/y (20.65%), respectively. The SY and its uncertainty estimated by the first-order uncertainty analysis at NSD and HSG sites are 6.9×10^5 t/y (17%) and 6.7×10^6 t/y (21%) respectively. Figure 8 shows the distribution of SY at the two sites obtained by the Monte Carlo simulations. The distributions at both the sites are positively skewed. The standard deviations of the simulated SY at the two sites are almost equal to that obtained from the first-order uncertainty analysis. The SY at NSD and HGS are estimated to be $6.9 \pm 1.2 \times 10^5$ t/y and $6.7 \pm 1.4 \times 10^6$ t/y, respectively, and the estimated 90% interval contains the observed values of 6.4×10^5 t/y and 7.2×10^6 t/y respectively.

5. Limitations

This study presents a methodology for quantifying uncertainty in the estimate of SE and SY for ungauged basins based on RUSLE-SDR approach. Uncertainties in SE and SY arise from uncertainties in data, model and due to stochastic nature of the soil erosion process. Like most of the previous studies (referred in Section 1), the proposed methodology accounts for only those sources of uncertainties that are available or could be quantified easily. For example, models/equations used for estimating R and LS do not provide sufficient details to ascertain model uncertainties, hence only data uncertainties are accounted for. On the other hand, uncertainties in data needed for estimating K and CP factors are not available. Hence, only model uncertainties are considered. Thus, the proposed methodology does not account for certain sources of uncertainties leading to under estimation of SE and SY prediction uncertainty. Further, the proposed methodology assumes spatial independence of certain RUSLE factors like R, L, S, C and P factors, resulting in further underestimation of SE and SY prediction uncertainty.

We have demonstrated the proposed methodology by applying it to Garra River basin. The basin has data restrictions that are typical of river basins in India. The spatial distributions of SE and SY for the study basin are obtained by using land use land cover data for 2005, which may not be a true representation of basin conditions during the study period (1962 – 2008). Further, the study has used gridded daily rainfall data available at a spatial resolution of $0.25^\circ \times 0.25^\circ$ obtained by interpolating rain gauge observations. The coarser spatial resolution of the data is not sufficient to capture

spatial variability of rainfall in the basin. In addition, the gridded rainfall data may have large interpolation errors, which are not accounted for because they are not available for the study basin.

In spite of many limitations, the proposed framework for quantifying and propagating uncertainties in SE and SY appears promising, particularly for ungauged basins in which sheet and rill erosion form the major component of total erosion.

6. Summary and Concluding Remarks

The main objective of this work is to present a methodology for quantifying uncertainties in the estimates of soil erosion (SE) and sediment yield (SY) at ungauged basins. A systematic procedure is provided for evaluating and propagating uncertainties in a RUSLE-SDR based approach for SE and SY prediction. Expressions for uncertainty propagation are derived using first-order uncertainty analysis making the proposed methodology viable even for large river basins. The novelty of the work lies in presenting a unified framework for quantifying uncertainties in SE and SY that is applicable to ungauged basins with storage structures. The methodology has been applied on the Garra River basin in India and the major conclusions derived from this study are listed below:

- (i) The SE in the basin is very high (23 ± 4.7 t/ha/y) with higher values in the upper mountainous region (92 ± 15.2 t/ha/y) than in the lower alluvial plains (19.3 ± 4 t/ha/y).
- (ii) The LS and CP factors govern the magnitude of soil erosion and its uncertainty in upper mountainous region and lower alluvial plains, respectively.
- (iii) Sediment delivery ratio (SDR) values for Nanak Sagar dam (NSD) and Husepur gauging station (HSG) are estimated to be 0.63 and 0.45, respectively, with about 5% uncertainty in both the estimates.
- (iv) The SY at NSD and HSG are estimated to be 6.9×10^5 t/y (17 %) and 6.7×10^6 t/y (21 %) respectively. The observed values at the two sites are 6.4×10^5 t/y and 7.2×10^6 t/y respectively, and they lie within estimated 90 % confidence interval. The results suggest that the proposed approach could be effective for sheet or rill erosion dominated Himalayan River basins like the Garra basin.

The uncertainty in SY derived from Monte Carlo simulations and first-order uncertainty analysis are very similar. The distributions of SY at both sites are positively skewed, although the magnitude of coefficient of skewness is small. Not all sources of uncertainties could be accounted for in the study because of limited data available. Hence, the estimated uncertainties in SE and SY are underestimation of true uncertainties. Review of uncertainties reported in the literature suggests that true uncertainty can be much higher than the predicted uncertainty. However, in absence of long records of observed SY, the quantification of true uncertainty remains a challenge.

Acknowledgements

The authors acknowledge the financial support provided by the Ministry of Earth Sciences, New Delhi under the Indo-UK joint programme on Changing Water Cycle. The first author also acknowledges the Ph.D. studentship from IIT

5 Kanpur.

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Tables

Table 5 Data used in the study and their specifications.

Sr. No.	Input Data	Name & Agency	Specifications	Reference
1	Digital Elevation Model (DEM)	SRTM (Shuttle Radar Topography Mission)	90 m spatial resolution; year 2001; database version 4.1	Jarvis et al. (2008)
2	Land use and land cover	National Remote Sensing Center (NRSC)	1:50,000 scale; year 2005	NRSC (2006)
3	Soil		56 m spatial resolution; year 2005	National Bureau of Soil Survey (NBSS)
4	Annual average rainfall	India Meteorology Department (IMD)	0.25° spatial resolution; daily gridded rainfall data set from 1901 to 2013)	Rajeevan and Bhate (2009)

Table 6 Equations and their references for estimating RUSLE factors, sediment erosion, and sediment delivery ratio (SDR). Expressions are also given for quantifying and propagating uncertainty based on first-order analysis.

Factor	Estimation of Factor	Estimation of Uncertainty
R	$R = (79 + 0.363 \times r) \times 9.8$ (a) (Babu et al. 1978)	$\delta R = 3.558 \times \delta r$ (b)
K	$100K = 2.1 \times 10^{-4} \times (12 - OM) \times M^{1.14} + 3.25 \times (sc - 2) + 2.5 \times (p - 3)$ (c) (Wischmeier and Smith, 1978)	$\delta K = \text{Calculated} - \text{Measured}$ $= 0.0026$ (65 % Confidence Interval) (Wischmeier and Smith, 1978)
L	$L = \frac{(\lambda_{i-1} + D)^{m+1} - (\lambda_{i-1})^{m+1}}{D(22.13)^m}$ (d) (Wischmeier and Smith, 1978; Desmet and Govers, 1996)	$\frac{\delta L}{L} = \sqrt{\left(\frac{m}{\Delta x} \delta \Delta x\right)^2 + (\ln(m+1) \delta m)^2}$ (e) where, $\delta m = \frac{\Delta m}{2\sqrt{6}}$ (Triangular distribution)
S	$S = 10.8 \times \sin\theta + 0.03$ for slope < 9%; $S = 16.8 \times \sin\theta - 0.05$ for slope $\geq 9\%$ (f) (McCool et al., 1987)	$\delta S = 10.8 \times \cos\theta \times \delta\theta$ slope < 9% , $\delta S = 16.8 \times \cos\theta \times \delta\theta$ slope $\geq 9\%$ (g) $\delta\theta = \sqrt{\left(\frac{\delta\Delta h}{\Delta x \times \left(1 + \left(\frac{\Delta h}{\Delta x}\right)^2}\right)}\right)^2 + \left(\frac{-\delta\Delta x}{\Delta h \times \left(1 + \left(\frac{\Delta x}{\Delta h}\right)^2}\right)}\right)^2}$ (h)

C	Reference tables (Morgan, 2009; FAO, 1978)	$\delta C = \frac{\Delta C}{2\sqrt{6}}$ (Triangular distribution) (i)
P		$\delta P = \frac{\Delta P}{2\sqrt{6}}$ (Triangular distribution) (j) (JCGM, 2008)
SDR	SDR = $1.42 \times A^{-0.132}$ (k) (Sharda and Ojasvi, 2016)	$\delta SDR_{\text{model}} = \sqrt{(\exp(se^2) - 1) \times \exp(2 \ln(SDR) + se^2)}$ (l) where, se = standard error (0.048) $\delta SDR_{\text{input data}} = 0.18 \times A^{-1.132} \times \delta A$ (m) where $\delta A = n \times 2\Delta x \times \delta \Delta x$ $\delta SDR = \sqrt{(\delta SDR_{\text{model}})^2 + (\delta SDR_{\text{input data}})^2}$ (n)

C, the cover and management factor is the ratio of soil loss from an area with specified cover and management to that of an identical area in tilled continuous fallow; **ΔC**, difference between upper and lower limit of C factor; **CV**, the coefficient of variation; **CS**, the coefficient of skewness; **Δh**, maximum difference in the elevation between the given cell and its neighbor cells (8 neighboring cells in D8 algorithm); **δΔh**, elevation error in DEM (3.17 m); **K**, the soil erodibility factor, expressed in the units of ton ha hr MJ⁻¹mm⁻¹ ha⁻¹; **L**, the slope length factor, is the ratio of soil loss from the field slope length to that from a 22.1meters length under identical conditions; **λ**, field slope length in meters; **δλ**, uncertainty in field slope length; **M**, Particle-size parameter [% silt x (100 - % clay)]; **m**, variable slope-length exponent (0.3 – 0.5); **δm**, uncertainty in variable slope-length exponent; **n**, number of cells contributing to one cell; **OM**, organic matter content (%); **P**, the support practice factor, is the ratio of soil loss with a support practice like contouring, strip cropping, or terracing to that with straight-row farming up and down the slope; **p**, permeability class (rapid = 1, moderate to rapid = 2, moderate = 3, slow to moderate = 4, slow = 5, very slow = 6); **ΔP**, difference between upper and lower limit of P factor; **r**, the average annual rainfall in mm; **R**, the rainfall runoff erosivity factor, expressed in the units of MJ mm ha⁻¹ hr⁻¹ y⁻¹; **S**, the slope steepness factor, is the ratio of soil loss from the field slope gradient to that from a 9-percent slope under otherwise identical conditions **sc**, soil structure code (very fine granular = 1, fine granular = 2, coarse granular = 3, blocky, platy or massive = 4); **SE**, the computed soil erosion per unit area expressed in t ha⁻¹ y⁻¹; **SY**, the sediment yield at a location in the basin, expressed in t y⁻¹; **θ**, slope of the terrain in degrees; **Δx**, distance between the given cell and the neighboring cell having maximum elevation difference; **δΔx**, geo-location error in DEM (5.17 m)

Table 7 C factor for different land use and land cover classes along with their uncertainties.

LULC Class	C Factor Range	Mean Value	Uncertainty
Forest	0.001 – 0.002	0.0015	13.61%
Grassland	0.01 – 0.02	0.015	13.61%
Urban	0.05 – 0.1	0.075	13.61%
Plantation/Orchard	0.1 – 0.3	0.2	20.41%
Crops (Double & Triple)	0.3 – 0.5	0.4	10.21%
Crops (Kharif, Rabi & Zaid)	0.3 - 1	0.65	22%

Wasteland	0.4 – 0.6	0.5	8.16%
Water/Snow	0	0	0

Table 8 Different cropping practice (P) factor for various cropping practice along with their uncertainties.

Crop Practice	P-Factor Range	Mean value	Uncertainty
Strip Cropping	0.6 – 0.9	0.75	8.16%
Terrace Cropping	0.35 – 0.45	0.4	5.1%
Other Areas	1.0	1.0	0%

Table 5 Comparison of uncertainties in RUSLE factors and soil erosion (SE) reported in the literature and those obtained in the present study. The present study employs forward uncertainty propagation for the Garra river basin.

Factor	Reference	Range of uncertainty	Scale	Method	Present study
R Factor	Catari 2010	7 – 16 %	Basin	Forward	3.4 – 6.7 %
	Catari et al. 2011	8.9 – 10 %	Basin	Forward	
	Wang et al. 2002b	30 – 40 %	Basin	Forward	
K Factor	Catari 2010	5 – 90 %	Basin	Forward	5.4 – 9.6 %
	Parysow et al. 2003	25 – 35 %	Plot	Forward	
	Wang et al. 2001	5 – 25 %	Basin	Backward	
LS Factor	Mondal et al. 2016	3 – 12 %	Basin	Forward	2 – 12 %
	Wang et al. 2002a	0 – 15 %	Plot	Forward	
CP Factor	Hession et al. 1996	10 %	Plot	Backward	8.2 – 13.6 %
	Tetzlaff & Wendland 2012	23 %	Basin	Backward	
	Tetzlaff et al. 2013	23 %	Basin	Backward	
Soil Erosion	Biesemans et al. 2000	1.7%	Basin	Forward	11 – 29 %
	Catari 2010	10 – 20 %	Basin	Forward	
	Hession et al. 1996	40 – 50 %	Plot	Forward	
	Risse et al. 1993	57 – 62 %	Plot	Backward	
	Tetzlaff et al. 2013	34%	Basin	Forward	
	Tetzlaff & Wendland 2012	34%	Basin	Forward	

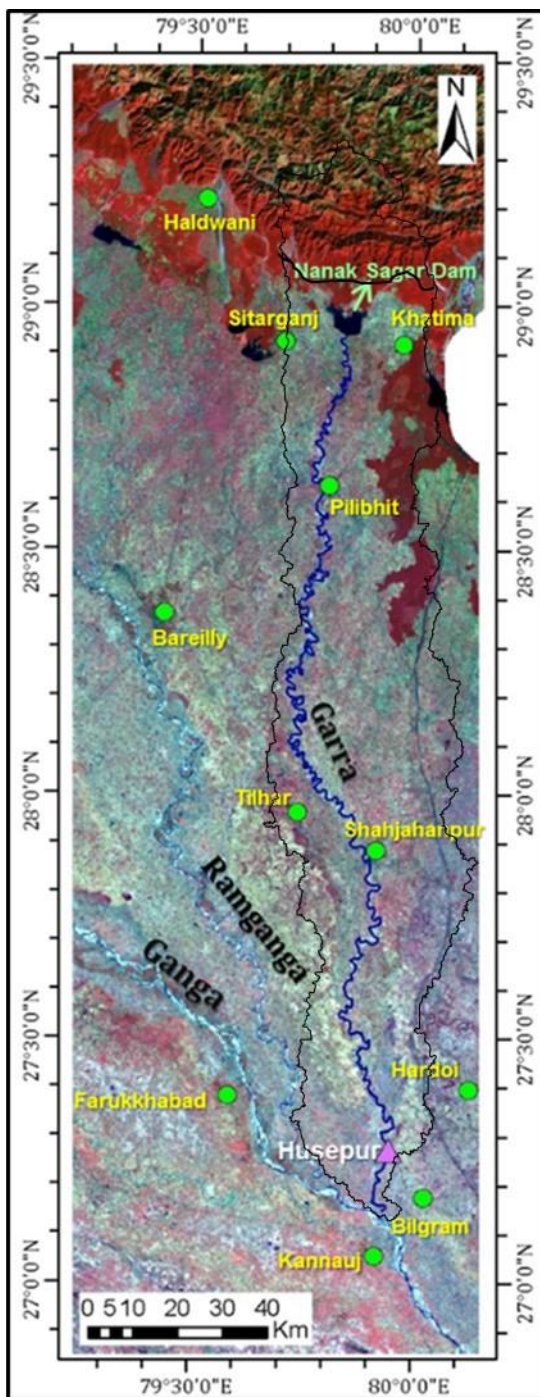


Figure 3 LANDSAT image (1999-2000) in false color composite showing the Garra River basin. The major neighboring rivers (Ganga & Ramganga), location of major cities, the gauging station (Husepur) and the major water structure (Nanak Sagar Dam) are also shown

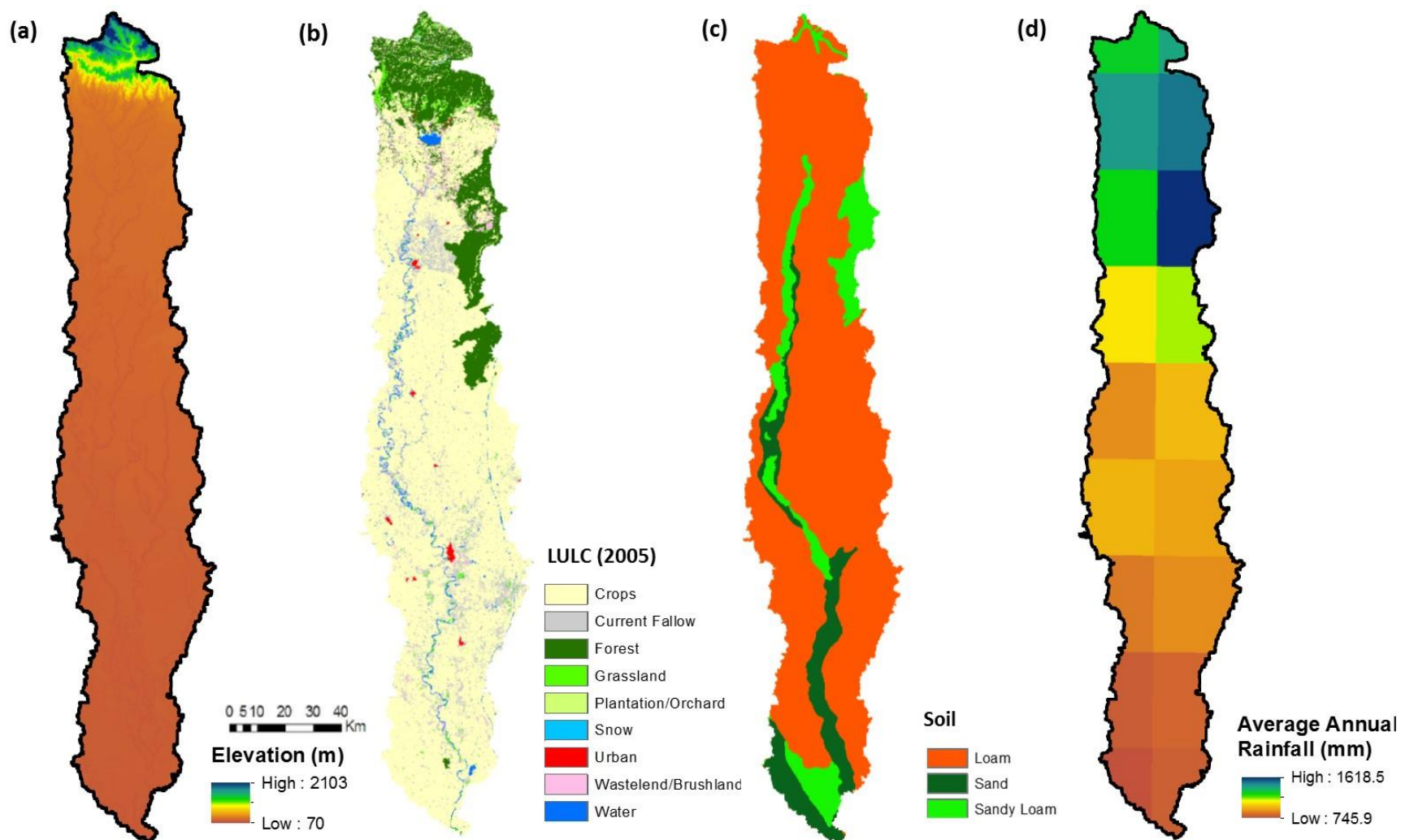


Figure 4(a) Elevation (SRTM, 90 m) (b) LULC and (c) Soil data from NRSC (2005) and (d) Average annual rainfall (1962 – 2008)

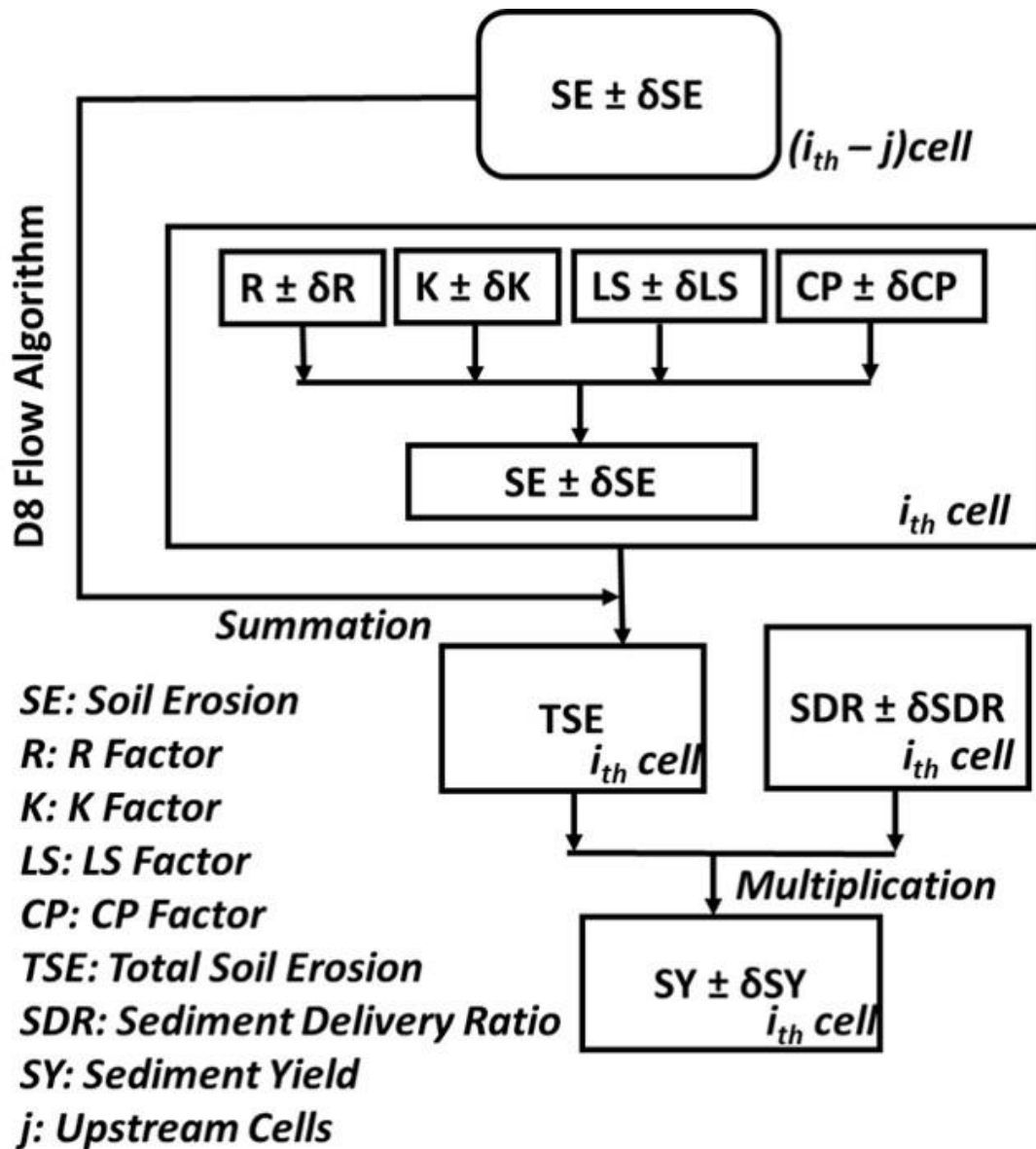


Figure 5 Approach to estimate soil erosion and sediment yield with associated uncertainties

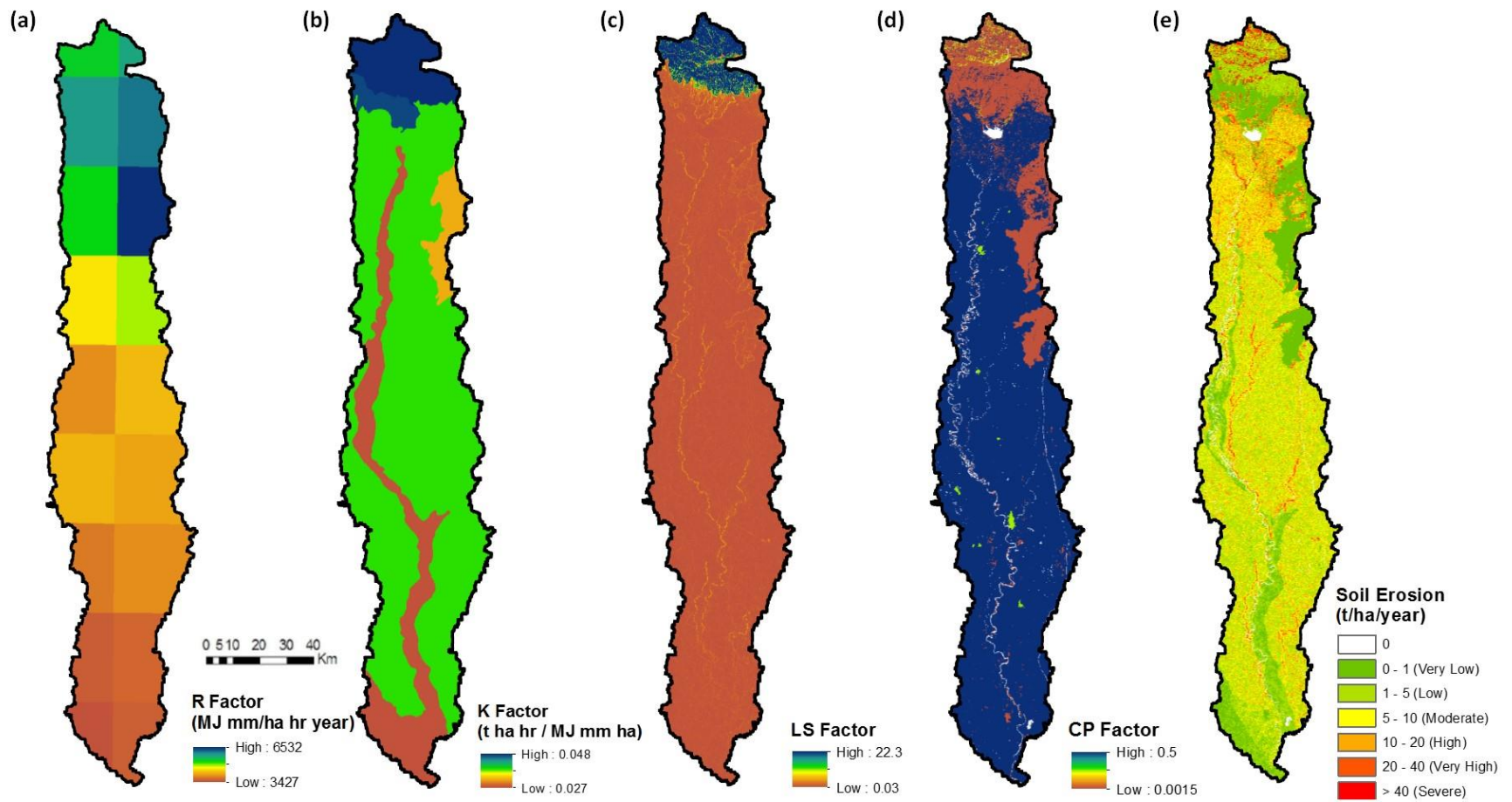


Figure 6 (a) **Rainfall runoff erosivity (R)** (b) **Soil erodibility (K)** (c) **Topographic steepness (LS)** (d) **Crop practice (CP) factors**, and (e) **Soil Erosion estimation** for the Garra River basin

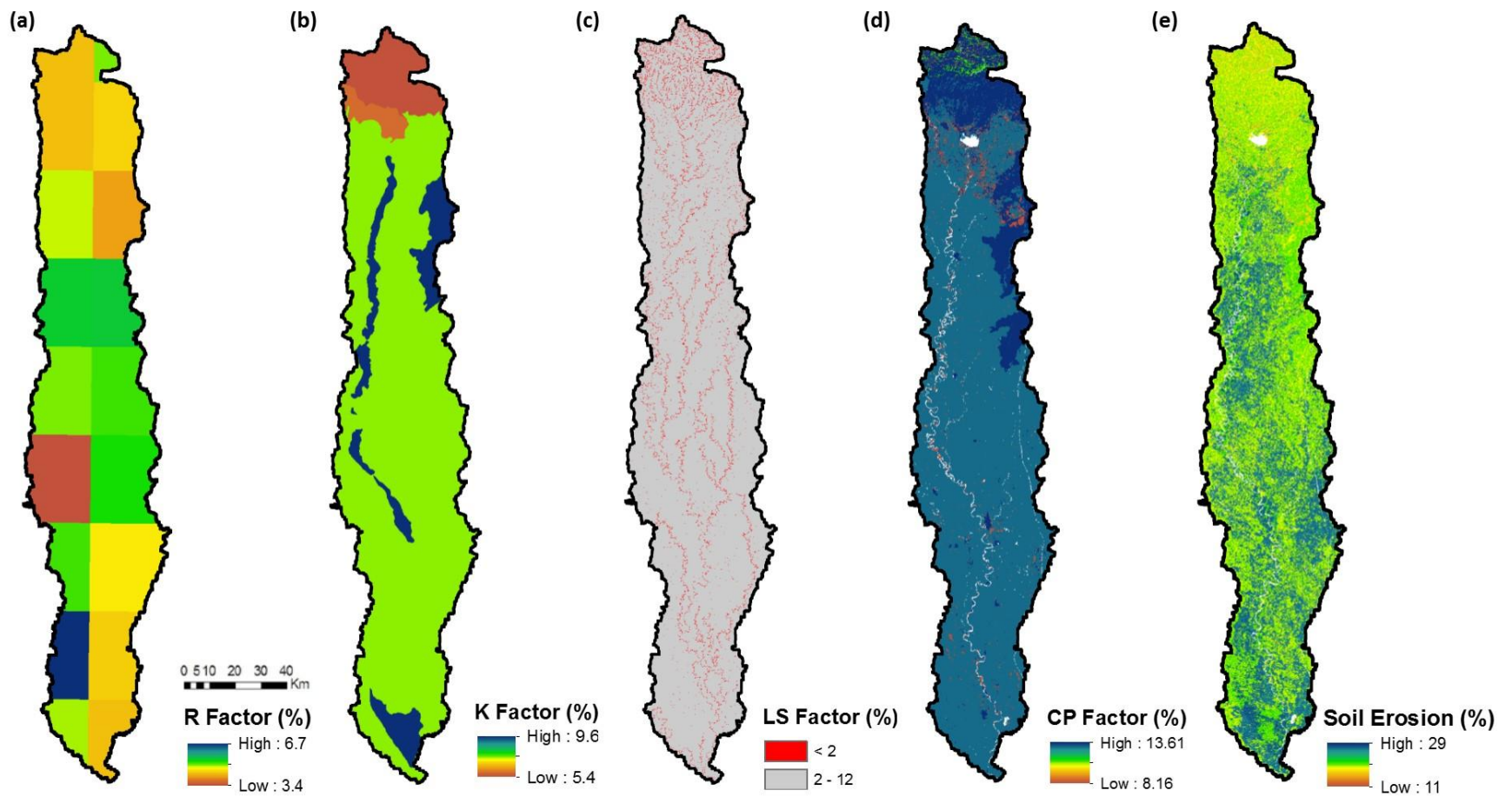


Figure 7 Percentage uncertainty in (a) Rainfall erosivity (b) Soil erodibility (c) Topographic steepness (d) Crop and practice and (e) Soil erosion uncertainty in percentage for the Garra River basin

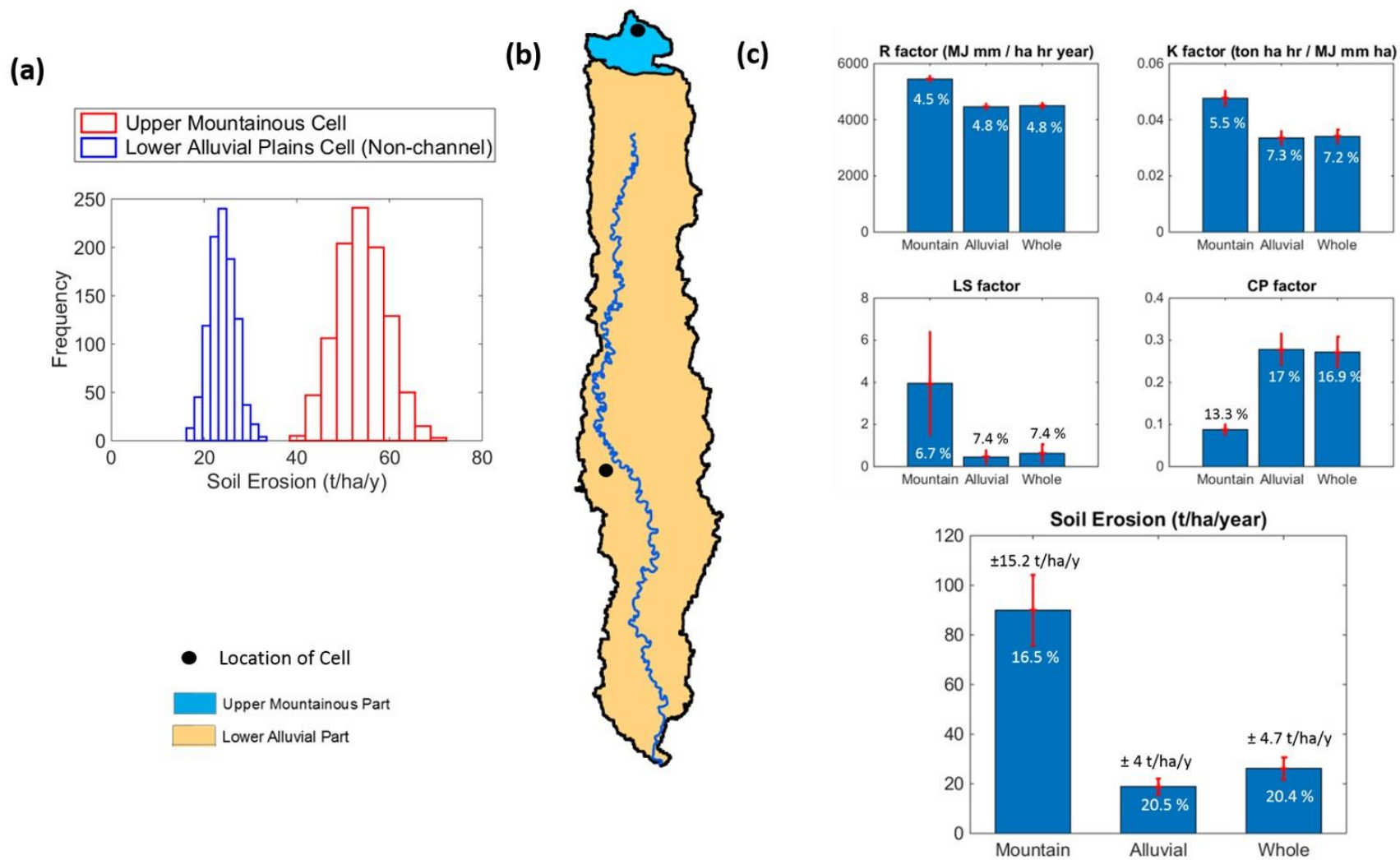


Figure 8 (a) distribution of SE at their representative cells in the basin namely, upper mountainous part and lower and lower alluvial part (b) Upper mountainous and alluvial plains part of the basin (c) comparison between the different factors of RUSLE and SE for both region

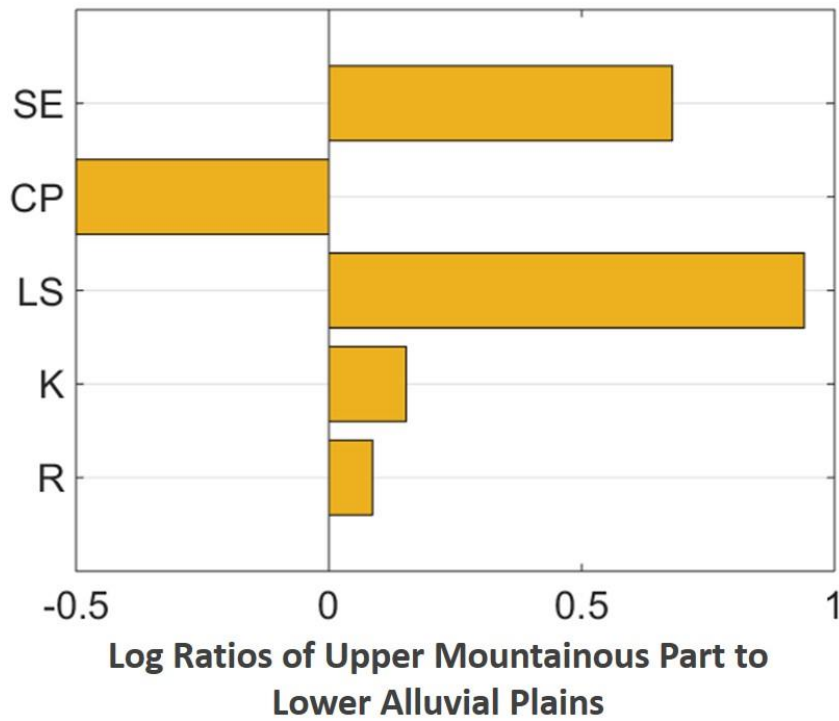


Figure 7 Comparison of RUSLE factors (R, K, LS & CP) and SE rates (SE) for upper mountainous and lower alluvial plains in the study basin

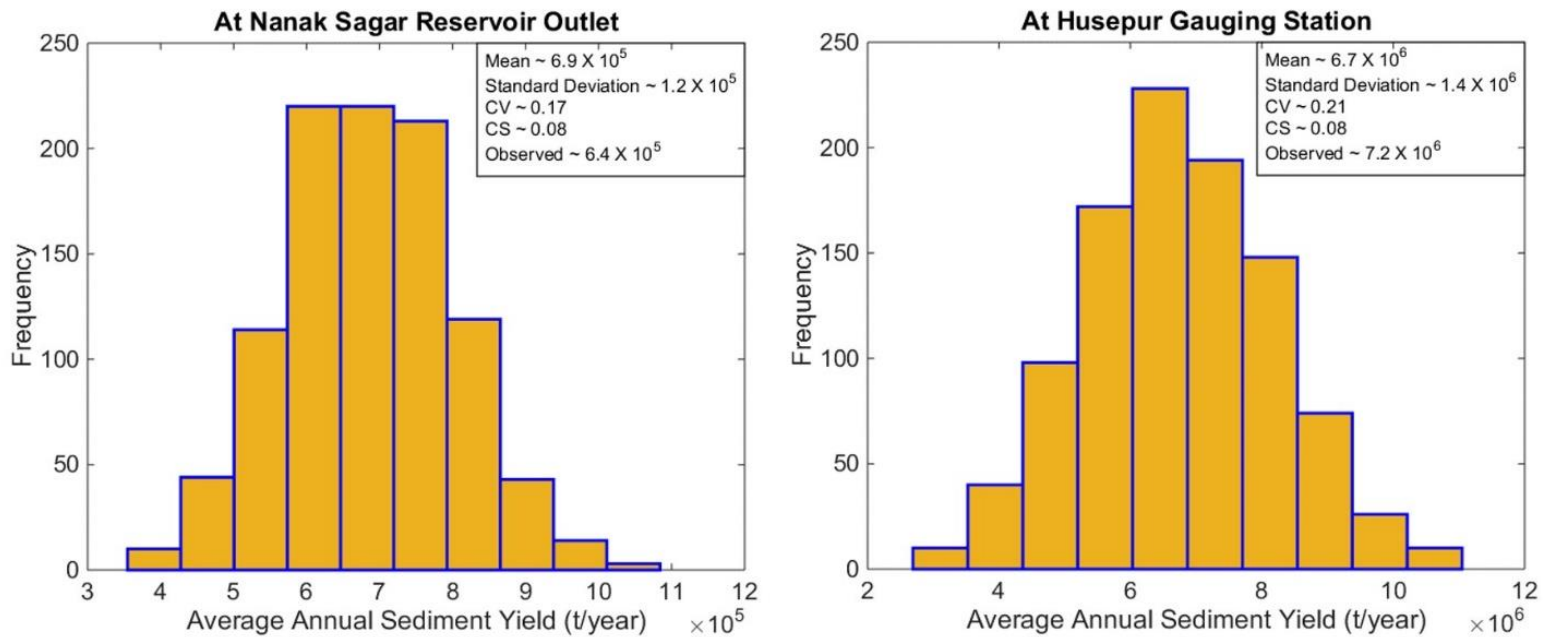


Figure 8 Histogram of annual average sediment yield (SY) at Nanak Sagar dam and Husepur gauging station based on Monte Carlo simulations. The mean, standard deviation, and coefficient of variation of the simulated SY and observed SY at the two sites are given in the legend