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Towards improved USLE-based soil erosion modelling in India: a review of prevalent pitfalls and implementation of exemplar methods

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Abstract

One of the most common approaches to modelling soil erosion worldwide has been the implementation of the original Universal Soil Loss Equation (USLE) and its revised version, the RUSLE. However, despite its widespread use, often there are discrepancies in the methods used to compute it and in the values elicited for the five individual factors that comprise this function. Such pitfalls subsequently skew the final results obtained and often many studies also fail to adequately examine the accuracy of the enumerated soil loss amounts. We examine these aspects with respect to the raft of USLE-based studies undertaken in India over the last few decades, reviewing a total of 100 investigations in this regard. Results reveal that almost all studies had either over- or underestimated at least one of the five factors, thereby possibly misrepresenting the actual soil loss occurring from their examined areas. Even more worryingly, most studies had failed to document their methods succinctly or in sufficient detail to ascertain their efficacies or provide viable templates for replication elsewhere. Our results also show a marked spatiality in the pursuance of such studies, with these being mostly undertaken in the eastern part of the country, even though the proportionate land affected by soil erosion is considerably less in this region. Thus regions

where the USLE would be most pertinent for implementation towards land management have seen a lower number of applications. We hope that by avoiding the missteps highlighted in this paper and following the subsequently detailed exemplar methods of conducting such an investigation along with the relevant model accuracy and uncertainty checks, the USLE can be best utilised in these regions and in the rest of the country for soil erosion mitigation. Though focused on India, the methods outlined can also be used to conduct the most accurate possible USLE-based soil erosion modelling elsewhere.

Keywords: Universal Soil Loss Equation; land degradation; runoff and sediment yield; factor estimation accuracy; rainfall erosivity; land management

1. Introduction

Like most countries in (sub)tropical and semi-arid climes, soil erosion by water (overland and channelised) is a primary agent of land degradation in India too (Lal, 2001; Bhattacharyya et al., 2015, 2016). About 68.4% of the nation's degraded tracts experience accelerated soil erosion at rates greater than 10 t ha^{-1} yr^{-1} (NAAS, 2010). A recent pan-Indian sediment budget study (Sharda and Ojasvi, 2016) estimated a gross average annual soil erosion rate of 15.6 t ha^{-1} yr^{-1} that removes 5.11±0.4 billion tonnes of soil per year. About 22.9±29% of this volume passes into the marine realm, 34.1±12% gets deposited in reservoirs while the remaining 43.0±41% are held within inland sinks. About 40% of the country has a soil loss tolerance of less than 7.5 t ha^{-1} yr^{-1} while this is below 10 t ha^{-1} yr^{-1} for 70% of it (Sharda et al., 2013). The aforementioned pan-Indian average soil erosion rate of 15.6 t ha^{-1} yr^{-1} thus paints a rather bleak picture of land degradation country-wide, even taking into account the marked spatial variability in regional rates due to the ambient climatic and physiographic diversity. The existent soil loss results in considerable on-site and off-site effects, manifesting, respectively, in production losses valued at ca. $1 billion in 1989 (Reddy, 2003) and ~$2.5 billion in 2010 (Sharda and Pradeep, 2013), with the concomitant reservoir sedimentation decreasing the average capacity by ca. 1% (Sharda and Ojasvi, 2016) annually. Aptly therefore, in a recent global review of soil erosion modelling studies (Borrelli et al., 2021), India ranked third worldwide after USA (537 studies) and China (450 studies) with 161 studies.

Soil erosion models help in identifying erosion-susceptible areas, estimate erosion rates and discern possible causes behind its occurrence, thereby contributing towards land management. Such models can have relatively simple empirical approaches, like the Universal Soil Loss Equation or USLE (Wischmeier and Smith, 1965, 1978), which has also been supported theoretically thereafter (Ferro, 2010) or be physically-based (e.g. Pandey et al., 2016; Hancock and Wells, 2021). The USLE (Wischmeier and Smith, 1965, 1978) and the Revised USLE or RUSLE (Renard et al., 1991, 1993, 1997) stand out as the most frequently and widely used soil erosion models by far (Alewell et al., 2019; Borrelli et al., 2021). Their spatial applications have ranged from individual field parcels (Swerts et al., 2019; Fiener et al., 2019) to country-wide studies (Almaw Fenta et al., 2019; Koirala et al., 2019) and even across the entire planet's land surface (Borrelli et al., 2017, 2020).

The USLE/RUSLE has been employed to accomplish multifarious objectives related to soil erosion worldwide, including, but not limited to, modelling of future soil erosion scenarios with respect to projected land cover and climate conditions (e.g. Borrelli et al., 2017, 2020), ascertaining the most appropriate soil conservation strategies (e.g. Kabanza et al., 2013; Galdino et al., 2015), land use planning (e.g. Haregeweyn et al., 2017; Liu et al., 2020), simulation of soil organic carbon flux and sequestration potential (e.g. Ito, 2007; Mandal et al., 2020) and to assess the global market impacts of soil erosion (e.g. Sartori et al., 2019). The presence of a huge body of scientific literature and a high degree of flexibility in terms of data requirements promotes these methods' adaptability to and applicability in data-sparse conditions (Benavidez et al., 2018; Alewell et al., 2019). It is therefore unsurprising that the seminal works of Wischmeier and Smith (1965, 1978), who developed the USLE, have been cited a staggering 10989 times while those of Renard *et al.* (1991, 1997) on the RUSLE had 5755 citations at the end of 2020. Not only do process-based models have far larger data requirements, they are not necessarily better than the USLE in estimating soil erosion (Kinnell, 2010; Alewell et al., 2019), and for large-scale soil erosion assessments, no other model is as suitable as the USLE (Borrelli et al., 2017, 2020).

India is projected to experience increased annual rainfall as well as intensified localised heavy downpour spells (Kulkarni et al., 2020), besides potentially undergoing marked land cover changes in the near future (Bhattacharyya and Sanyal, 2019). As these environmental changes are expected to aggravate soil erosion problems around the world (Borrelli et al., 2017, 2020), there is a genuine case for undertaking targeted scenario-based soil erosion modelling in India, for which the USLE is most suitable. However, data unavailability/inaccessibility pose serious challenges this regard, even though the country stood fifth worldwide with 67 papers on USLE, after USA (274), China (218), Brazil (88) and Italy (87) in a recent global meta-analysis on USLE-type soil erosion modelling (Alewell et al., 2019).

Therefore, the objectives of this review are to identify existing bottlenecks to using the USLE in India, highlight the missteps apparent in previous attempts and propose best model parameterisation methods based on state-of-the-art data, along with relevant model evaluation options to foster effective and accurate USLE applications herein. Since this review does not attempt to explore or analyse the subtleties of the USLE-type modelling approach, any interested reader is referred to the Agricultural Handbook No. 537 (Wischmeier and Smith, 1978) for USLE and No. 703 (Renard et al., 1997) for RUSLE, as well as review articles that have either discussed the model development history (Laflen and Moldenhauer, 2003; Laflen and Flanagan, 2013), scrutinised the logic and science behind the USLE-modelling approach (Alewell et al., 2019; Kinnell, 2019), outlined appropriate parameterisation methods for different regions across the world (Benavidez et al., 2018; Ghosal and Das Bhattacharya, 2020) or proposed other contributions towards further development of the model concept (Kinnell, 2008, 2010, 2014). While this review only considers Indian studies, we perceive that some of the methodological missteps apparent in them may also be present in USLE/RUSLE applications elsewhere. Thus this review can aid anyone employing the USLE for soil erosion research and also highlight future possibilities for model refinement by pointing out current data deficiencies.

2. A brief account of the USLE/RUSLE

Generally speaking, the USLE was developed to be a cornerstone of soil and water conservation in the United States after measuring and analysing soil losses due to water erosion from thousands of field plots and small catchments since the 1930's, considering rainfall parameters, topography, soil characteristics, cropping and management practices (Wischmeier and Smith, 1965, 1978). It was the result of a statistical analysis involving 10,000 plot-years of runoff and soil loss data from 49 stations across the USA. As the quintessential example of an empirical model [which has also been theoretically endorsed (Ferro, 2010)], the USLE does not simulate soil erosion rates using physical equations describing the detachment, transport and deposition of soil particles but instead uses a simple multiplicative equation that was devised by identifying statistically significant relationships between the assumed important variables and measured soil loss data. These data were collected from plots that were up to 122 m long with slopes ranging between 3% and 18%, having different cropping and management practices, and were compared to soil losses from 22.1 m long and 1.83 m wide 'unit plots' having 9% slope and maintained in a continuous regularly tilled fallow condition with up-and-down hill tillage, which was taken to represent the 'worst-case scenario' for soil erosion. The unit plot was thus used as a baseline condition to which the topographic attributes and cropping, management and conservation practices of all other plots were compared in order to establish relationships between the occurring soil erosion and its influencing factors (Wischmeier and Smith, 1965, 1978; Renard et al., 1997, 2011).

In SI units, the USLE calculates the long-term average annual soil erosion rate in t ha^{-1} yr^{-1}, through a simple multiplication of six model parameters or factors, viz. rainfall-runoff erosivity (R factor), soil erodibility (K factor), slope length and steepness (LS factor), cover and management (C factor) and support practice (P factor). Of these six factors, only the R factor has an original unit, i.e. MJ mm ha^{-1} h^{-1} yr^{-1}, while the unit of the K factor (t ha h ha^{-1} MJ^{-1} mm^{-1}) is merely the soil loss rate per unit of the R factor, and the rest are dimensionless. The LS is the slope length and steepness factor in relation to unit plot conditions, the C factor is defined as the ratio of soil loss from a field with specific cover and management to that from a field under clean-tilled continuous fallow unit plot conditions and P**,** the support practice factor, is the ratio of soil loss with a specific support practice to that from an up-and-down-slope tillage culture of unit plots. Notably, the values of the C and P factors range from zero for completely erosion-resistant conditions, to unity for the worst-case unit plot conditions (Wischmeier and Smith, 1965, 1978). In sum, the USLE uses four dimensionless factors to modify the soil loss as described by dimensioned rainfall erosivity and soil erodibility factors (Renard et al., 1997). These dimensionless LS, C and P factors highlight the model's utility as a key decision making tool in land and water management, as they pertain to plausible precursors of erosion that can actually be managed in order to reduce soil loss to below the permissible tolerance rates.

Originally devised to ascertain the best cropping practices to reduce erosion from agricultural fields (Wischmeier and Smith, 1965), the USLE was updated over the next decade to provide techniques for estimating the respective factor values for additional land uses, climatic conditions, irregular terrain and management practices (Wischmeier and Smith, 1978). In later years, owing to widespread use of the USLE within and outside the USA, its limitations became apparent, quite important among which was its inability to accurately estimate soil erosion in rangelands (Spaeth et al., 2003; Renard et al., 2011).

A need for updating the USLE was therefore felt and the RUSLE came into being (Renard et al., 1991, 1997). Its development benefitted from the previously identified limitations as well as from an improved understanding of the physics of rill and interrill erosion under natural and simulated rainfall (Renard et al., 1997, 2011). Although the equation remained the same, a comprehensive revision of the factor estimation methods was undertaken, the most significant of which was the new subfactor-based approach in the C factor estimation, which promoted RUSLE applications in any land use. The RUSLE also introduced process-based relationships to improve parameterisation and allowed sub-annual calculation of the R, K and C factors, in addition to including a new term 'rill to interrill erosion ratio' in the LS factor estimation and provided new P-values applicable to both croplands and rangelands. Above all, the RUSLE was a shift towards computerised (DOS-based) erosion modelling from the 'paper-based' approach of the USLE (Renard et al., 1997, 2011).

The latest version, RUSLE2, is a full-blown Windows-based program, with substantially advanced modelling capabilities and application possibilities, compared to the original USLE as well as the RUSLE (Renard et al., 2011). However, having been developed to estimate rill and interrill erosion rates from relatively small plots or catchments, the RUSLE2, like its predecessors and many other soil erosion models, is unable to simulate gully erosion.

3. USLE applications in India: facts and figures

According to the database that we prepared, which consists of research articles published in journals indexed in the Web of Science, Scopus or Scimago databases, as well as theses and conference papers, the USLE is by far the most used soil erosion model in India, with 115 applications between 1991 and 2020 (see Tables S1 and S2 in the Supplementary Information file). It has been applied to estimate soil erosion rates at all spatial scales ranging from an open pit mine (Nigam et al., 2017) and large river basins (Karan et al., 2019; Bhattacharya et al., 2020a,b) to districts (Srinivas et al., 2002; Thelkar et al., 2019), states

(Mandal and Sharda, 2011a; Mahapatra et al., 2018) and the entire country (Singh et al., 1992; Maji et al., 2008; Sharda et al., 2013). Its temporal applications have been just as diverse, ranging from individual rainstorms (Kothyari and Jain, 1997; Jain and Kothyari, 2000) to decadal and centennial erosion projections with respect to climate change scenarios (Mondal et al., 2015, 2016a; Gupta and Kumar, 2017; Khare et al., 2017; Pal and Chakrabortty, 2019; Chakrabortty et al., 2020).

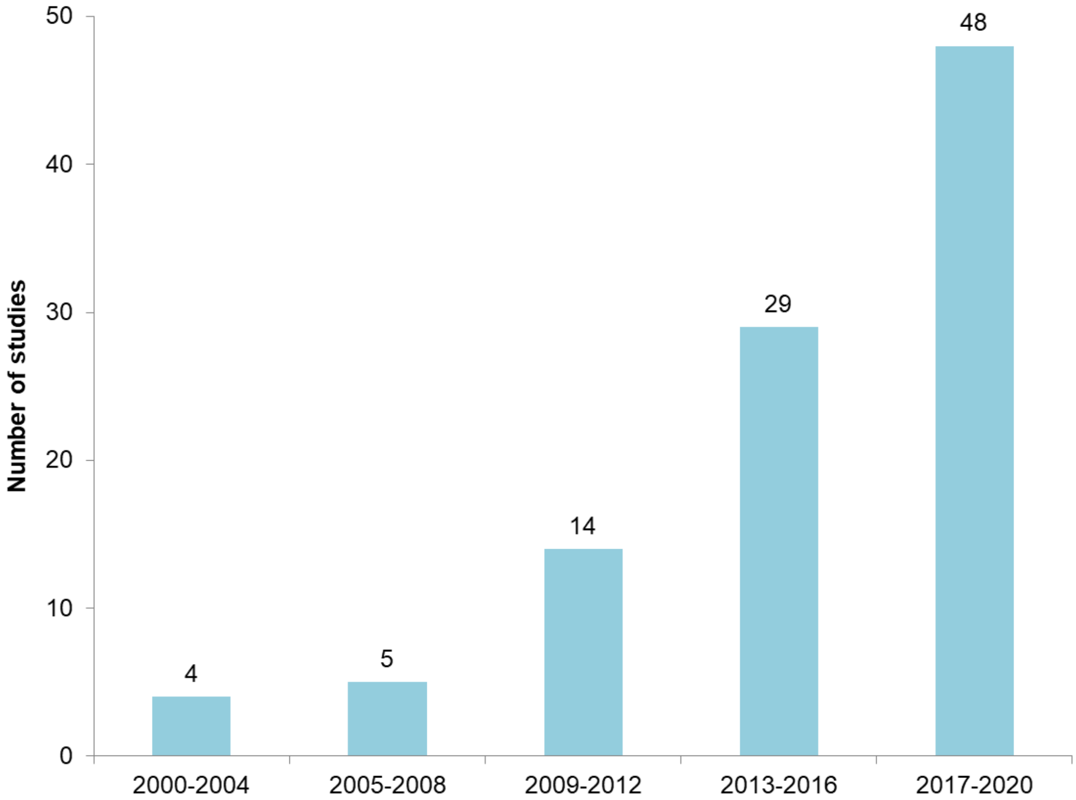

Fig. 1: Trend of published studies using the USLE in India

Note: See Table S1 in the Supplementary Information file for details about each study

For this review, we have considered 100 of the 115 studies that were collated, excluding those articles (the details of which are given in Table S2 in the Supplementary Information file) that used the USLE but did not provide any details on factor estimation, or studies that assessed the erosion risk after keeping one of the factors as a constant and not estimating the same, or studies that performed event-scale soil erosion modelling, as the USLE is ill-suited for this (Wischmeier and Smith, 1978; Kinnell, 2010). These 100 studies (see Table S1 in the Supplementary Information file for individual details on each of them) were carried out in 24 different states across India between 2000 and 2020, with the highest number of publications (16) being in 2018. The number of publications first increased sharply during 2009-2012 and between 2017 and 2020, a USLE-based paper was published on average, once every month (Fig. 1).

The peninsular plateau and its fringe areas are the most erosion susceptible physiographic region of India (Singh et al., 1991, 1992) and naturally most of the studies we reviewed (n=73) were conducted in various parts of it. Apart from this, 15 studies were based in the Himalayas, three were situated in the hills of the Northeast and the remaining ones had modelled soil erosion in the northern plains (n=4), eastern coastal plains (n=3) and western coastal plains (n=2) (Fig. 2). An overwhelming 84% of the papers had implemented the USLE at the catchment scale, the smallest and largest of these basins encompassing 7.31 km^2 and 41285 km^2, respectively (Fig. 2) (mean catchment area = ca. 4200 km^2, standard deviation = ca. 8000 km^2). Of the remaining 16 studies, one had used the USLE at the plot-scale, three others had employed it at the hillslope-scale and 12 studies had modelled soil erosion in administrative units (i.e. sub-districts, districts or states). Overall, 52 studies clearly stated why it was important or necessary to undertake soil erosion modelling in their respective study area, while 48 did not provide such a rationale. Our reviewed studies (Table S1) had used the model to accomplish a variety of objectives– 54 investigations simply aimed to obtain a soil erosion map, 10 studies used the model for subwatershed prioritisation, in nine cases the USLE-derived soil loss estimates were compared to that predicted by other modelling approaches, five studies employed it to propose erosion control measures, 14 studies performed multi-temporal soil erosion modelling (with seven of them comprising future erosion projections), three studies each had used the model to obtain an approximation of reservoir sedimentation rates and study the effect of DEM resolution on erosion modelling while two studies had assessed the model uncertainty and performance at the catchment- and plot-scale respectively (Fig. 2).

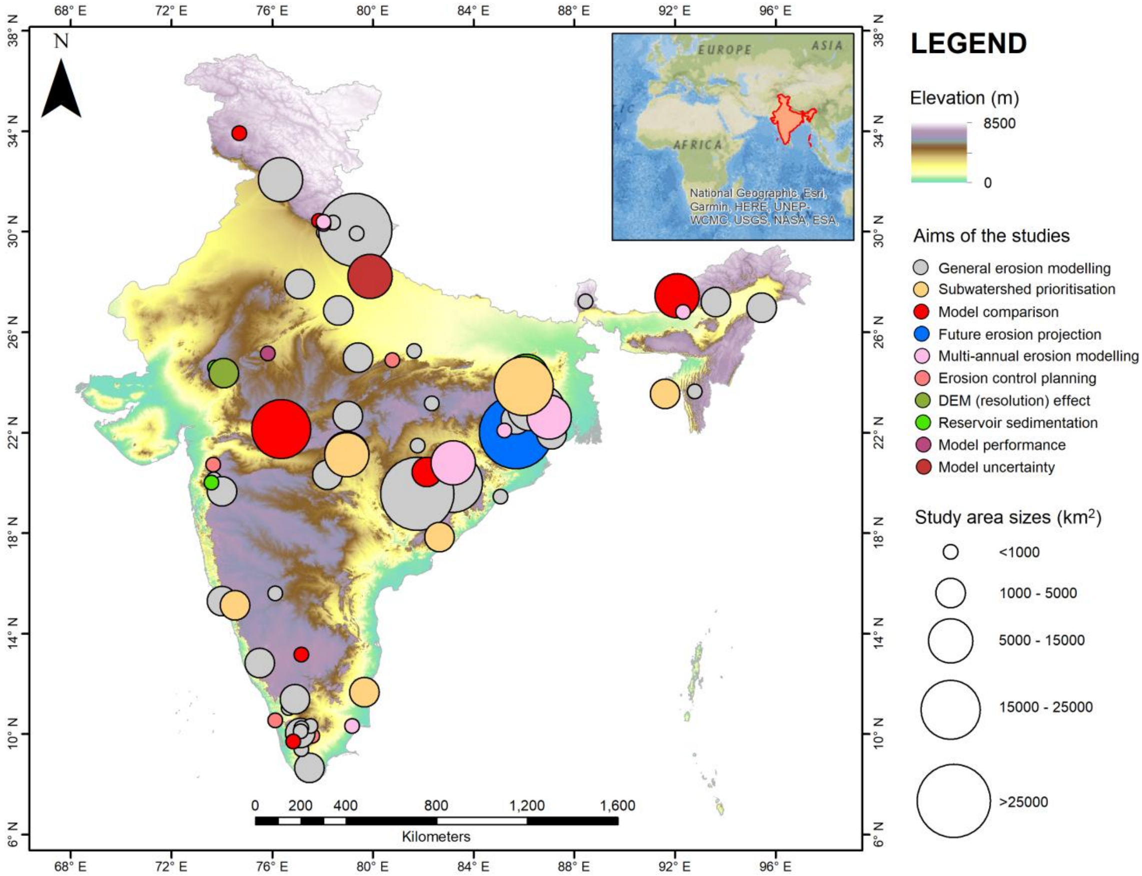

Fig. 2: Aims of the reviewed USLE applications and the location and size of their respective study areas Note: For details of the respective study locations and areal coverage, see Table S1 in the Supplementary Information file.

Sharda et al. (2013) compared the USLE-modelled erosion rates (Maji et al., 2008) to soil loss tolerances (Mandal and Sharda, 2011b) across the entire country, and delineated areas of erosion risk while also calculating extents under the various erosion control priority classes for different states of India. As opposed to a simple soil erosion map (Singh et al., 1992; Maji et al., 2008), their state-wise comparative assessment of erosion rates and tolerances is far more informative and highlights more pertinently the regions under various levels of erosion risk. We thus used data from their study (share of state-wise to country-wide priority erosion risk area) as well as information gathered by us during this review (location of the reviewed USLE applications; Fig. 2) to examine if the spatiality (focus or target areas) of the reviewed USLE applications was appropriate (i.e. applied in the most erosion-prone regions) (Fig. 3).

What becomes apparent from the above is that despite the raft of soil erosion investigations employing the USLE across India and the diverse aspects/viewpoints considered, the method is not being applied where it is probably the most pertinent. There is a clear concentration of studies in eastern India and the largest study areas are also found therein (Fig. 2). However, the eastern Indian states of West Bengal, Jharkhand and Odisha are not at the highest risk to soil loss nationwide (Sharda et al., 2013; Fig. 3). Jharkhand and West Bengal lead the country in terms of USLE applications with 15 and 13 studies, but rank 9th and 23rd, respectively, among 28 states, in terms of area under erosion control priority (Sharda et al., 2013). Conversely, Uttar Pradesh and Andhra Pradesh have the largest erosion priority areas but are 10th and 13th, respectively, in terms of studies conducted therein (Fig. 3). In four states (Uttar Pradesh, Karnataka, Sikkim and Nagaland) more than 80% of the eroded area is classed under one of the priority categories for conservation (Sharda et al., 2013; Fig. 3), despite which, these areas have received little attention (just four studies each in Uttar Pradesh and Karnataka, one in Sikkim and none in Nagaland). Less than 30% of the studies reviewed were conducted in states where more than 65% of the total eroded area is deemed to be of conservation priority (i.e. in Andhra Pradesh, Arunachal Pradesh, Assam, Karnataka, Nagaland, Sikkim, Uttar Pradesh and Uttarakhand).

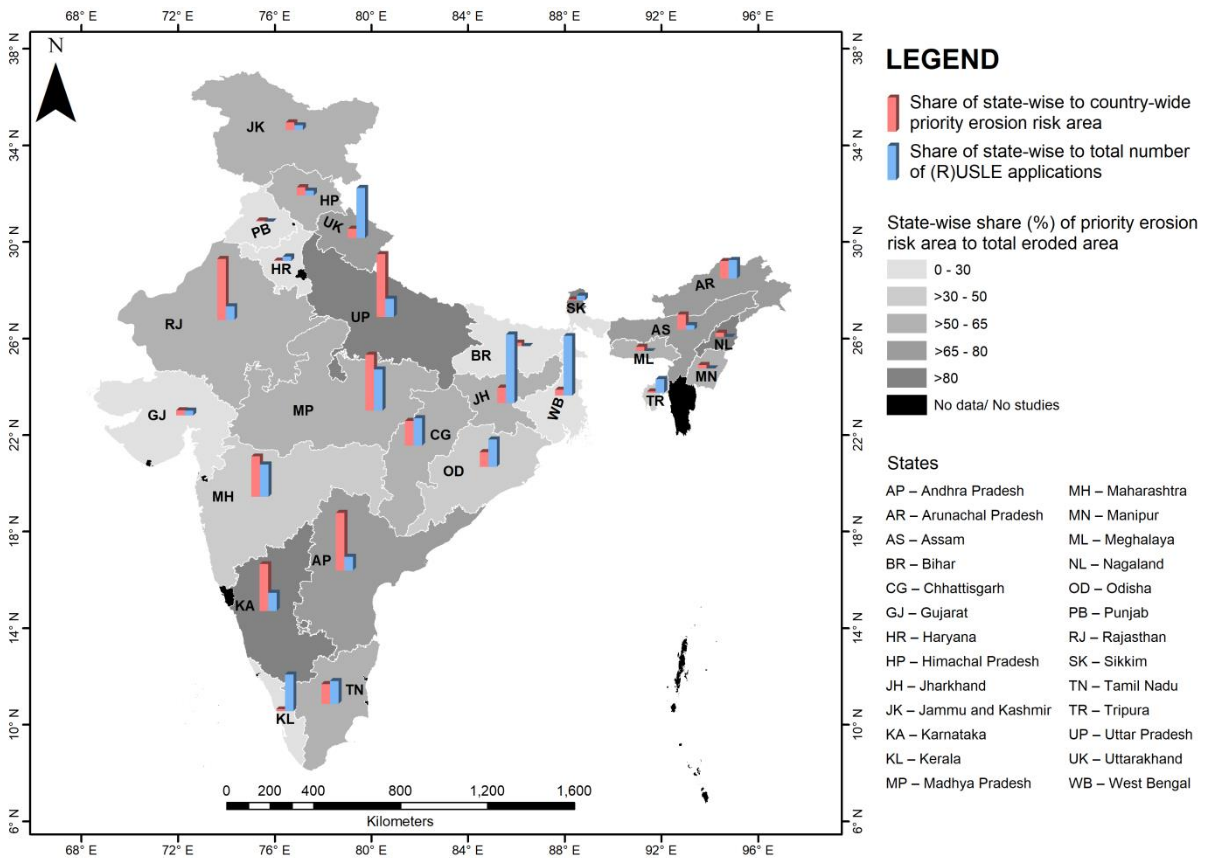

Fig. 3: State-wise comparison between share of total priority eroded area and share of total number of studies

4. USLE applications in India: factor-wise review

After reviewing all the papers scrupulously it was apparent that very few studies had attempted to evaluate the elicited results. Thus, we have particularly emphasised on assessing the model parameterisation methods stated in each paper as a measure of the efficacy of their derived results, with respect to the actual modelling procedures outlined in Agricultural Handbook Nos. 537 (Wischmeier and Smith, 1978) and 703 (Renard et al., 1997), as well as in seminal review articles on USLE (Renard et al., 2011; Benavidez et al., 2018; Alewell et al., 2019; Kinnell, 2019). We discerned that across the 100 studies examined (see Table S1), a total of 32 different methods had been used to estimate the various model parameters– 12 for the R factor, six each for the K and LS factors and four each for the C and P factors. There were also instances where one or more of the factor estimation methods was not sufficiently described or their sources misquoted. We visualised the frequency with which each method was used by means of a chord diagram, rather than simple bar graphs, as this further allowed assessment of the frequency of co-occurrence of the various methods. Since in one USLE application, five methods can be combined to form 10 pairs (${}^{5}C_{2}$ = 10), we could derive 1000 such pair-wise combinations from the reviewed 100 studies. These 1000 combinations were grouped into 263 unique combinations, where the minimum and maximum frequency of co-occurrences was 1 and 24 respectively (Fig. 4). Among these, 95 pair-wise combinations were found only once and 200 of the 263 unique combinations occurred less than six times (Fig. 4).

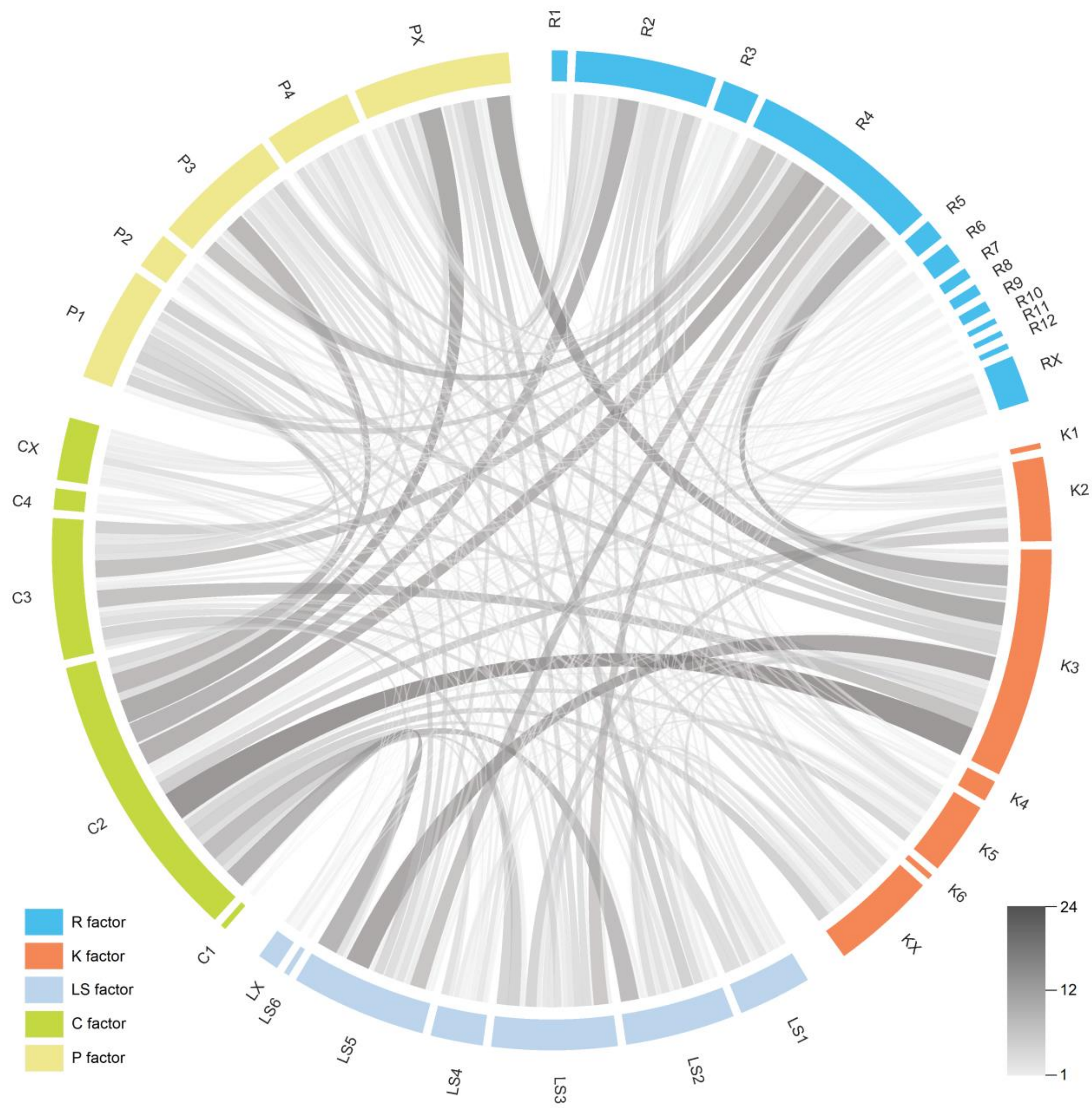

Fig. 4: Grouped chord diagram illustrating the 263 unique pair-wise combinations of USLE factor estimation methods. The width of a sector is indicative of the frequency with which that method was used in the studies reviewed, and the shades of grey demarcating the chords highlight the frequency of occurrence of a particular pair, ranging between 24 and 1. For details on the method-wise codes, refer to Table Nos. 1 (for R factor), 2 (for K factor), 3 (for LS factor), 4 (for C factor) and 5 (for P factor), and see the ensuing subsections for a detailed analysis.

4.1 Computations of the R factor

The R factor captures the potential erosive effect of rainfall and the ensuing runoff on the topsoil. Devised by Wischmeier (1959), the annual R factor, also termed as 'Rainfall Erosion Index', is a product of two rainfall factors, i.e. the total storm kinetic energy (E) and the maximum 30-minute rainfall intensity (I_{30}), summed over a year for all storms of over 12 mm rainfall or for downpours expending more than 6.5 mm rainfall within 15 minutes, and taking the average of those annual values for at least 22 years. Since the R factor can only be calculated as an average over decadal timescales, the USLE is ill-suited to simulate event-scale soil erosion (Kinnell, 2010). If successive storms have an interval of at least 6 hours, they are considered to be separate events and storms debouching rainfall amounts less than 12 mm are not considered (unless 6.5 mm fell within 15 minutes), as sufficient runoff capable of causing erosion is unlikely to be generated in such a scenario. However, this can also depend on the ambient antecedent moisture conditions in the area and so may need to be evaluated separately, if required.

The kinetic energy of a rainstorm is calculated using equations that link E to I, which in USLE were of logarithmic nature for rainfall intensities less than 76 mm h^{-1} (for I > 76 mm h^{-1}, a constant value was proposed) (Wischmeier and Smith, 1978) while in the RUSLE, an exponential relationship replaced the logarithmic equation, this being valid for all rainfall intensities (Brown and Foster, 1987). The E is indicative of the volume of rainfall and runoff, while the I_{30} indicates peak detachment and runoff rates. The EI_{30} term therefore captures both particle detachment and transport capacity (Wischmeier and Smith, 1978; Renard et al., 1997). The R factor estimation method is almost identical in both the USLE and RUSLE, apart from the change in the kinetic energy equation and correction for ponding on flat slopes in the RUSLE. The R factor takes the unit of MJ mm ha^{-1} hr^{-1} yr^{-1} in SI units (Foster et al., 1981).

Although the USLE/RUSLE can only predict on-site soil erosion and not off-site catchment sediment yield as runoff is not categorically considered in the R factor (Alewell et al., 2019), the EI_{30} term was found to be the most strongly correlated of the considered rainfall parameters that measures soil loss at the plot-scale, andcan explain between 72–97% of the variations in soil loss caused by individual rainfall events (Wischmeier and Smith, 1978; Renard et al., 2011). However, the lack of individual storm records and sub-hourly data for the recommended long periods in many parts of the world, especially in the Global South, has often precluded the use of the prescribed USLE/RUSLE methods for R factor estimation and triggered the development of simple regression equations or other empirical methods [such as the Modified Fournier Index (Arnoldus, 1977, 1980)] that enable R factor estimation using annual/monthly rainfall data (Benavidez et al., 2018; Alewell et al., 2019). Apart from the apparent constraint of massive data requirements to compute the R factor, there also exists the matter of its universal relevance, especially in the tropics. The larger median drop size of tropical rainstorms as well as their higher rainfall intensities and kinetic energies might lead to underestimation of the R factor in the tropics when calculated as per the EI_{30} method (Lal et al., 1980; Nyssen et al., 2005).

Of the 100 papers we reviewed, 73 studies clearly mentioned the temporal extent of the rainfall data used, which ranged between 1 and 113 years, with an average data record of 20.67 years. In all, 92 papers provided information about their rainfall data source, 78 of which used point-scale rainfall data obtained from weather stations in and around their study area, nine studies used any one of the various open-source gridded rainfall datasets available (e.g. India Meteorological Department (IMD), Tropical Rainfall Measuring Mission (TRMM), Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), WorldClim or others), three studies measured rainfall erosivity as per the stipulated USLE method while in the remaining two cases, approximate rainfall erosivity values were obtained from the iso-erodent map of India (Babu et al., 1978, 2004). Exactly half (39) of the 78 papers that used weather station data, detailed the interpolation method used to generate an R factor map from the point-scale data. The deterministic interpolation methods of Inverse Distance Weighting and Thiessen's polygons were used in 21 and nine studies, respectively, and eight studies performed kriging (however no information on the kriging variant or variogram modelling was shared by any of these studies), while in one study a trend surface map was created.

Table 1: Summary of the various methods employed to quantify rainfall erosivity for USLE-based soil erosion modelling in India

Code in Fig. 4	Source	Method	Location of development	No. of studies used
R1	Wischmeier and Smith (1978)	$\boldsymbol{R = \frac{\sum_{i=1}^{j}(EI_{30})_i}{N}}$ $(EI_{30})_i$: Product of rainfall kinetic energy (E) and 30-minute maximum rainfall intensity (I_{30}) for storm i. j: number of storms in an N-year period (suggested minimum period is 22 years) Original unit: 100 foot-tonf inch $acre^{-1}$ h^{-1} yr^{-1}, but depends on units of measurement of E and I_{30}.	USA	3
R2	Babu et al. (1978)	$\boldsymbol{R = 79 + 0.363P}$ P: annual precipitation (mm) Original unit: t-m cm ha^{-1} h^{-1} yr^{-1}	India	27
R3	Babu et al. (2004)	$\boldsymbol{R = 81.5 + 0.38P}$ P: annual precipitation (mm) Original unit: t-m cm ha^{-1} h^{-1} yr^{-1}	India	7

R4	Arnoldus (1977, 1980)	**R based on Modified Fournier Index** $\sum_{i=1}^{12}\frac{P_i^2}{P}$ P: annual precipitation (mm) P_i: monthly precipitation (mm) Original unit of the MFI-based equations: t-m cm ha^{-1} h^{-1} yr^{-1}	Western Africa and Western USA	6
R4	Unclear	$\boldsymbol{R = 1.735 \times 10^{(1.5 log_{10}(MFI) - 0.8188)}}$ *MFI*: Modified Fournier Index Unit: unclear	Unclear	31
R5	El-Swaify et al. (1987) as cited in Benavidez et al. (2018)	$\boldsymbol{R = 38.5 + 0.35P}$ P: annual precipitation (mm) Units: t ha^{-1} $year^{-1}$ (all the other factors must have been developed to be dimensionless so that the final soil loss is in t ha^{-1} $year^{-1}$)	Possibly Thailand	4
R6	Roose (1977) as cited in Renard and Freimund (1994)	$\boldsymbol{R = (0.5 \pm 0.05)P}$ P: annual precipitation (mm) Original unit: 100 foot-tonf inch $acre^{-1}$ h^{-1} yr^{-1}	Western Africa	4
R7	Renard and Freimund (1994)	$\boldsymbol{R = 0.0483P^{1.610}}$ **(if** P**<850 mm)** $\boldsymbol{R = 587.8 - 1.219P + 0.004105P^2}$ **(if** P**>850 mm)** Unit: MJ mm ha^{-1} h^{-1} yr^{-1}	Western USA	2
R8	Panigrahi et al. (1996) as cited in Shinde et al. (2011) and Sundara Kumar et al. (2018)	$\boldsymbol{R = P^2(0.00364 log_{10}P - 0.000062)}$ P: annual precipitation (mm) Unit: MJ mm ha^{-1} h^{-1} yr^{-1}	India	2
R9	Babu et al. (1978, 2004)	**R values from Iso-erodent map of India** Unit: t-m cm ha^{-1} h^{-1} yr^{-1}	India	2
R10	Nakil (2014) as cited in Nakil and Khire (2015)	$\boldsymbol{R = 839.15 exp(0.0008P)}$ P: annual precipitation (mm) Unit: MJ mm ha^{-1} h^{-1} yr^{-1}	India	1
R11	SARH (1991) as cited in Ghoshal and Das Bhattacharya (2020)	$\boldsymbol{R = -0.0334P + 0.006661P^2}$ P: annual precipitation (mm) Unit: MJ mm ha^{-1} h^{-1} yr^{-1}	Mexico	1
R12	Sudhishri and Patnaik (2004) as cited in Dash et al. (2019)	$\boldsymbol{R = 0.82P - 6.61}$ P: annual precipitation (mm) Unit: t-m cm ha^{-1} h^{-1} yr^{-1}	India	1
RX	Unclear	N/A	N/A	9

A total of 12 different methods were used in the reviewed works to estimate the R factor (Table 1). We obtained R factor values from the tables and maps of those studies that explicitly mentioned the same, and compared these values to the rainfall erosivity values for the respective study areas as estimated in the Global Rainfall Erosivity Database (GloREDa) (Panagos et al., 2017). The GloREDa R factor map (resolution ~1 km; unit: MJ mm ha^{-1} h^{-1} yr^{-1}) for the Indian subcontinent was prepared through geostatistical interpolation of high resolution rainfall kinetic energy and intensity data of 247 stations that are well-distributed throughout India, with an average temporal coverage of 7 years. It is till date the best available rainfall erosivity map for India and we have used it to examine the relative accuracy of the various methods employed in the reviewed studies to estimate rainfall erosivity at the catchment- and regional-scale in India (Fig. 5), with particular emphasis on the regional specificity and units of the same. We finally compared 88 studies in this manner, leaving out plot- and hillslope-scale USLE applications (as evaluating the R factor value of such small area studies would not be feasible using the GloREDa map that is of far coarser resolution) as well as studies that did not report their R factor values.

A non-parametric Wilcoxon rank-sum test was conducted for the entire sample of 88 studies to assess the presence of any statistically significant difference between the rainfall erosivity values as obtained from the sampled studies and that derived from GloREDa. The results of this test express a highly significant difference ($p < 10^{-15}$) between the two, highlighting the overall underestimation of rainfall erosivity in these studies. We did not perform similar tests to compare the rainfall erosivity values summarised for each of the methods used as not all of the methods were used sufficiently or equitably to guarantee a minimum or roughly equal sample size for group-wise comparison of means. A graphical comparison appeared to be more meaningful instead (Fig. 5).

With 31 applications, the equation cited by Tiwari et al. (2015), based on the Modified Fournier Index (Arnoldus, 1977, 1980) is the most frequently used R factor derivation method. Arnoldus (1977) had developed the equation as–

$$\boldsymbol{R = 1.735 \times 10\ (1.5 log_{10}(MFI) - 0.8188)} \qquad \text{(Eq. 1)}$$

to compute approximate rainfall erosivity for Morocco, in units of t-m cm ha^{-1} h^{-1} yr^{-1}, and this equation has apparently been confused as–

$$\boldsymbol{R = 1.735 \times 10^{(1.5 log_{10}(MFI) - 0.8188)}} \qquad \text{(Eq. 2)}$$

and subsequently been widely misused in India. The Eq. 2 has even been used to create a rainfall erosivity map for the entire country (Tiwari et al., 2015). Since such a fundamental error was committed by these studies, further assessment of the units or values derived in them was deemed immaterial. For completeness' sake, this has still been shown in Fig. 5 (Code A), and is observed to undervalue the R factor.

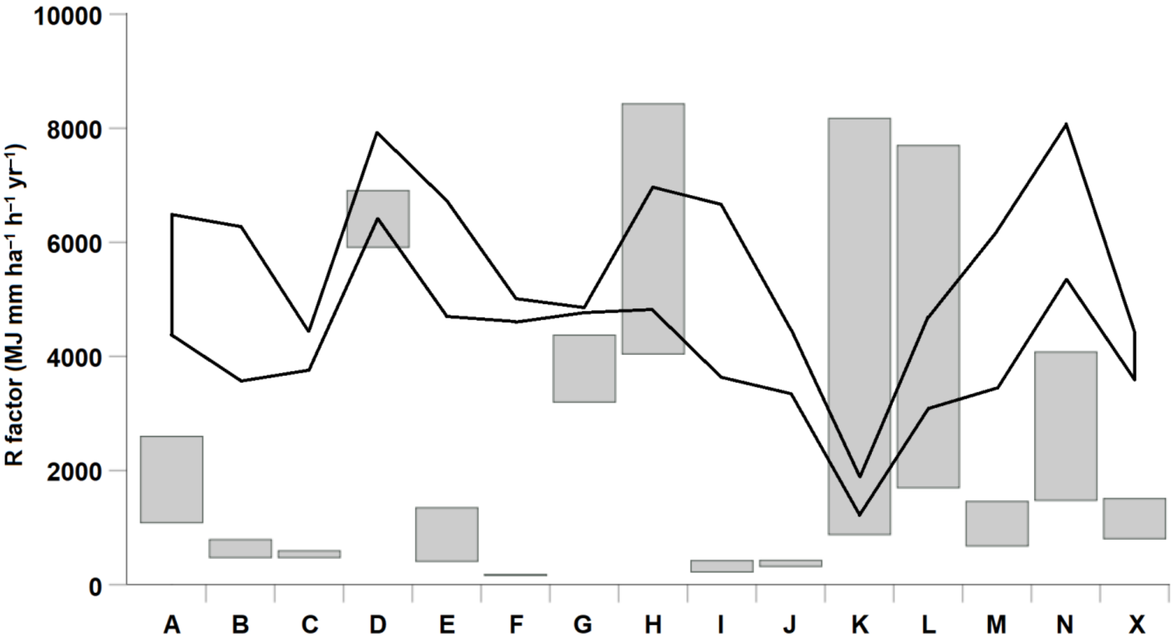

Fig. 5: Comparison of rainfall erosivity as estimated by various methods (high-low bars) in the reviewed studies and the GloREDa rainfall erosivity estimates (area graph). A: MFI-based equation used by Tiwari et al. (2015); B: Babu et al. (1978); C: Babu et al. (2004); D: Babu et al. (1978) with units corrected; E: Arnoldus (1980); F: El-Swaify et al. (1987); G: Wischmeier and Smith (1978); H: Renard and Freimund (1994); I: Panigrahi et al. (1996); J: Roose (1977); K: Roose (1977) with units corrected; L: Nakil (2014); M: Sudhishri and Patnaik (2004); N: SARH (1991); X: Method unclear.

Babu et al. (1978) devised a simple regression equation linking rainfall erosivity and annual rainfall using data from 42 stations across India. In all, 27 studies have used this method to compute the R factor, although only five of them have expressed their R values in the correct units of t-m cm ha^{-1} h^{-1} yr^{-1}. We could not succinctly assess if the other 22 studies had specifically converted their values from the metric units to the reported SI units of MJ mm ha^{-1} h^{-1} yr^{-1}, and therefore compared them separately. These 22 studies had underestimated the R factor by about nine times on average (Code B in Fig. 5). Since the multiplication factor to convert from metric to SI units is 10.2, we are quite certain that this underestimation stems from the misreporting of units. Contrarily, the other five papers that expressed their R factor in the correct units of t-m cm ha^{-1} h^{-1} yr^{-1} (that were converted to MJ mm ha^{-1} h^{-1} yr^{-1} for the comparison) differ on average from the GloREDa-extracted values by about 500 MJ mm ha^{-1} h^{-1} yr^{-1} (which could be due to differences in data resolution and measurement/computation aspects), and actually perform the best of all the methods sampled (Code D in Fig. 5) in quantifying the R factor. Just seven studies used the revised regression equation of Babu et al. (2004), and all of them reported their R factor values in SI units. These studies also underestimate (by about seven times) the rainfall erosivity, which again suggests that they possibly did not convert the derived values from metric to SI units (Code C in Fig. 5).

Six papers mention that they used the basic MFI, rather than one of the MFI-based equations that Arnoldus (1977, 1980) had proposed. This approach is inherently flawed, as the MFI is simply a ratio and not a method in itself, nor does it estimate the R factor in units of MJ mm ha^{-1} h^{-1} yr^{-1}. These six studies unsurprisingly underestimate the rainfall erosivity (Code E in Fig. 5). The method of El-Swaify et al. (1987: as cited in Benavidez et al., 2018) is rather odd, as it seemingly estimates the R factor in units of t ha^{-1} yr^{-1}, meaning that all other factors must be dimensionless. The implication for users looking to use such a method is that all six factors must be estimated as per the guidelines of the same source, rather than employing different methods to estimate different factors (which would then have varying and incompatible units). In our survey, four studies were found to use this equation, although none of them correctly quoted the source or reported the correct units corresponding to this method. Consequently, there is an average underestimation of the R Factor by a staggering 29 times across them (Code F in Fig. 5).

Following Roose (1977: as cited in Renard and Freimund, 1994), four studies actually estimated the rainfall erosivity as being equal to half of the annual precipitation. However, only one denoted the units correctly, i.e. 100 foot-tonf inch $acre^{-1}$ h^{-1} yr^{-1} and clearly converted the elicited values from the imperial to SI units using a multiplication factor of 17.3. However, it is apparent that this study grossly overestimated the R factor (Code K in Fig. 5). The other three studies did not convert the units and ended up underestimating the rainfall erosivity by more than 10 times (Code J in Fig. 5). The equations of Renard and Freimund (1994) (Code H in Fig. 5) and Nakil (2014) (Code L in Fig. 5) also overestimate the R factor, while that of SARH (1991) (Code N in Fig. 5), Panigrahi et al., (1996) (Code I in Fig. 5) and Sudhishri and Patnaik (2004) (Code M in Fig. 5) underestimate the same to various degrees. Biswal (2015) employed the regional R factor equation of Sudhishri and Patnaik (2004) but incorrectly reported the units to be in the SI system (instead of t-m cm ha^{-1} h^{-1} yr^{-1}), which could have led to its underestimation (Code M in Fig. 5). The eight studies for which the R factor estimation methods could not be understood, identified or otherwise verified also underestimated the erosivity on average (Code X in Fig. 5).

Three studies estimated the R factor as per the EI_{30} method of Wischmeier and Smith (1978), of which one was the plot-scale study of Ali and Sharda (2005) that we did not include in this comparison (due to its small areal extent that precludes sound judgement on the estimated R value from the GloREDa map which is of far coarser resolution). The other two studies, i.e., Pandey et al. (2007) and Singh and Panda (2017), respectively, underestimated and overestimated the R factor, and both taken together underestimated the rainfall erosivity (Code G in Fig. 5). This is surprising, as both these studies have reported R-values in the correct units and the GloREDa map, to which the values are being compared, was also developed in the same way. The discrepancy therefore, could arise from the short-term recording of pluviographic data in the respective studied locales, possibly at a low temporal resolution. However, some discrepancies may have also arisen due to data error ranges or uncertainty in both the GloREDa datasets and the actual measured rainfall erosivity values used in these studies.

Apart from the extensive confusion or lack of attention regarding assigning correct units to the various methods, the main issue with most of the studies' R factor estimation methods is their applicability in India. Considering that only 40 studies have estimated the rainfall erosivity using a method developed in India and just three more had attempted to measure the rainfall erosivity as per the USLE method, 57 studies had used methods that were developed elsewhere and hence calibrated for totally different climatic regimes. Of these 57 studies, only four reported the elicited values in the correct units. One of them estimated the R factor as per Roose (1977) and corrected the units, while the other three used the methods of SARH (1991) and Renard and Freimund (1994). However, none of them could estimate the R factor with any degree of accuracy (Codes H, K and N in Fig. 5), possibly because these methods are simply not suitable to quantify the rainfall erosivity in the Indian climatic scenario. Awareness of the regional specificity of the R factor estimation methods is especially important for Indian USLE users as there is a strong seasonality in the rainfall received (and hence, soil erosion) in the country and the rainfall regime is very dissimilar to that of the west coast of USA or western Africa for example, which is where Roose (1977), Arnoldus (1980) and Renard and Freimund (1994) had developed their respective methods.

4.2 Computations of the K factor

The K factor is the rate of soil loss per rainfall erosivity index for a specific soil, as measured in unit-plot conditions (Wischmeier and Smith, 1965, 1978) by keeping the LS, C and P factors constant at 1.0. It is a measure of the soil's capability to resist erosion, with higher values indicating higher erosion susceptibility and vice versa. Thus, the K factor is in effect a lumped parameter that captures the integrated effect of the soil properties (especially physical properties like texture, structure, porosity) that influence its erosional response. These are in effect, the soil hydraulic conductivity, permeability and total water capacity, as well as any other attributes that might influence soil particle detachment and transportation due to rainfall and the ensuing runoff (Wischmeier and Smith, 1965; Wischmeier and Mannering, 1969).

The best estimations of the K factor are obtained from long-term soil loss measurement on natural runoff plots, which is how it was originally determined (Wischmeier and Smith, 1965). However, as establishing, maintaining and monitoring runoff plots is an expensive affair, even for the minimal required period of two years (Renard et al., 2011; Alewell et al., 2019), the soil erodibility nomograph or its approximation equation is used in most cases to estimate the K factor. This requires data on the soil texture and organic matter content, along with information on soil structure and permeability (Wischmeier and Smith, 1978). The nomograph equation was reported to be quite accurate when used within its limits, i.e. for soils containing less than 70% silt and very fine sand and below 4% organic matter (OM) (Declercq and Poesen, 1992). Auerswald et al. (2014) have recently developed a set of equations that emulates and effectively replaces the nomograph or its approximation equation and can thus be used for the full range of soil properties. The earlier equation developed by Sharpley and Williams (1990) within the EPIC (Erosion Productivity Impact Calculator) model can also be used for the full range of soil properties. However, the universal applicability of the aforesaid K factor estimation methods can be questioned as both of them were developed by making use of plot-scale soil loss data from the US and thus perform best in medium textured, poorly aggregated soils of temperate regions. Irrespective of this, these methods have been the most frequently used worldwide (Benavidez et al., 2018), and understandably so, as efforts to come up with regionally or conditionally applicable K factor estimation methods or values have been largely unsuccessful or inconclusive, primarily due to the lack of long-term measured plot-level data (Alewell et al., 2019).

With a motive of increasing its global applicability, K factor estimation procedures were considerably revamped in the RUSLE (Renard et al., 1997). A new globally applicable soil erodibility index was included, which estimates this as a function of the geometric mean diameter of particles and specific equations were proposed for smectite-rich soils, soils with a clay-rich subsurface horizon and Hawaiian volcanic soils. Moreover, provisions were made to allow for interactions of the K factor with other factors (including the computation of a seasonal K factor) and the effect of surface stoniness (particles with >2 mm diameter) was explicitly included within this revamped K factor, rather than in the C factor, as was the case in the USLE. Further estimates of the K factor have also been devised subsequently (e.g. Bagarello et al., 2012). The unit of the USLE/RUSLE K factor in SI is t ha h ha^{-1} MJ^{-1} mm^{-1} (Foster et al., 1981).

Table 2: Summary of the various methods employed to quantify soil erodibility for USLE-based soil erosion modelling in India. All the equations in this table estimate the K factor in units of t acre h 100-$acre^{-1}$ ft^{-1} $tonf^{-1}$ $inch^{-1}$

Code in Fig. 4	Source	Method	No. of studies used
K1	Wischmeier and Smith (1978)	$\boldsymbol{K = \frac{A}{R}}$ A: soil loss rate; R: rainfall erosivity	1
K2	Wischmeier and Smith (1978), Renard et al. (1997)	**Standard soil erodibility nomograph**	16
K3	Wischmeier and Smith (1978), Renard et al. (1997)	$\boldsymbol{K = \left[2.1 \times 10^{-6} \times M^{1.14}(12 - a) + 0.0325(b - 2) + 0.025(c - 3)\right]}$ $M = (SIL + VFS) \times (100 - CLA)$ $SIL + VFS$: Mass fraction (%) of silt and very fine sand, i.e. particles with sizes between 2 and 100 µm. CLA: Mass fraction (%) of clay particles (<2 µm) a: soil organic matter mass fraction (%) b: soil structure code, viz. 1 (very fine granular), 2 (fine granular), 3 (medium or coarse granular), 4 (blocky, platy or massive) c: profile permeability class, viz. 1 (rapid), 2 (moderate to rapid), 3 (moderate), 4 (slow to moderate), 5 (slow), 6 (very slow)	44
K4	Sharpley and Williams (1990)	$\boldsymbol{K = \left[0.2 + 0.3exp\left(-0.0256SAN\left(1 - \frac{SIL}{100}\right)\right)\right] \times [\frac{SIL}{CLA + SIL}]^{0.3} \times \left[1.0 - \frac{0.25\,C}{C + exp(3.72 - 2.95C)}\right] \times [1.0 - \frac{0.7\,SN1}{SN1 + exp(-5.51 + 22.9\,SN1)}]}$ SAN, SIL, CLA and C are percentages of sand, silt, clay and organic carbon contents respectively, and SN1 is SAN divided by 100 and subtracted from 1.	4

K5	Stewart et at. (1975), Stone and Hilborn (2000), Das (2012)	**As a function of texture class and OM content**	14
K6	Singh et al. (1981) as cited in Vemu and Pinnamaneni (2011)	**K factor values corresponding to soil type**	1
KX	Unclear	N/A	20

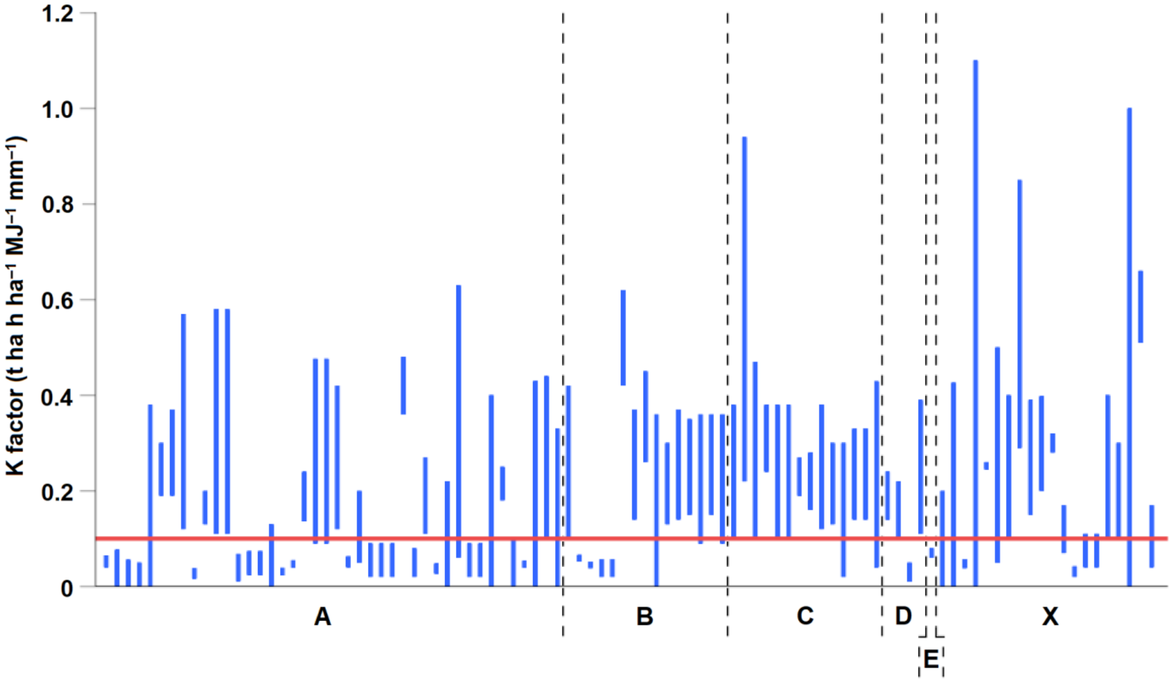

Fig. 6: K factor values as estimated by the reviewed studies. The red line indicates the maximum possible value of the K factor in SI units (0.1 t ha h ha^{-1} MJ^{-1} mm^{-1}). A: Wischmeier and Smith (1978) nomograph equation; B: Wischmeier and Smith (1978) standard nomograph; C: K factor tables of Stewart et at. (1975), Stone and Hilborn (2000) and Das (2012); D: Sharpley and Williams (1990) equation; E: From Singh et al. (1981) as per soil type; X: Method unclear

The methods employed to estimate the K factor in the reviewed studies are tabulated (Table 2). A total of 60 studies used the USLE standard nomograph or its associated equation, which is recommended for estimating the K factor in India (Singh et al., 1985). However, Ali and Sharda (2005) did not estimate the K factor by any set method but chose to actually measure it, which gives the most reliable account of the soil erodibility (Wischmeier and Smith, 1978; Renard et al., 1997, 2011). The accuracy of table-based (Stewart et al., 1975; Stone and Hilborn, 2000; Das, 2012) or equation-based (Sharpley and Williams, 1990) approaches to estimate the soil erodibility using soil textural and organic matter content data can however be questioned, given that these methods have no consideration of the soil structure or permeability, unlike the USLE standard nomograph.

Of the studies considered in this review, 74% had used soil maps to generate a K factor map, a quarter of the studies had estimated the soil erodibility from soil samples collected in the field, and one study had measured the K values from plot-scale soil losses. In all, 17 of the 25 studies that had estimated the soil erodibility from collected soil samples had adopted a stratified random sampling strategy. Except for three hillslope-scale applications in these 17 investigations, the soil samples for the other 14 studies had been collected from various soil types or geomorphic units (as ascertained from the respective soil/geomorphic maps) and the estimated K factor value was assigned to the entire corresponding soil or geomorphic unit. The remaining eight out of 25 studies had generated spatially-continuous K factor maps through interpolation but only two papers (Prasannakumar et al., 2011a, b) had clearly mentioned the interpolation technique used. In total, 91 studies had generated spatially-discrete K factor maps. Of these, 77 had either tabulated all the K factor values in their respective study area or the same could be noted from the provided maps. With a motive of assessing the accuracy with which these studies had been able to capture the spatial variability in the K factor, we calculated the average area under each K factor value, by dividing the areal extent of each study area by its denoted number of soil erodibility values, and compared the same with the known spatial variability in K factor in India (cf. Adhikary et al., 2014). In these 77 studies, the area under a singular K factor value ranged from as low as 0.695 km^2 (Singh and Panda, 2017) to a considerably larger extent of 20642.5 km^2 (Vemu and Pinnamaneni, 2011), with a mean of 1057 km^2 and standard deviation of 2711 km^2. However, in an isotropic scenario (variogram range and sill same in all directions), the soil erodibility is constant only up to ca. 50 km^2 in India (Adhikary et al., 2014). Judging by this, 60 of the 77 studies had failed to adequately capture the spatial variability in soil erodibility and had generalised the same to various extents, ranging from a minor 1.11 times (Pradeep et al., 2014) to a staggering 421 times (Vemu and Pinnamaneni, 2011), with the average being 27 times.

The other issue concerning the K factor estimation in India is overestimation. We found that 70 studies had partially or wholly transgressed the physical limit of the K factor in SI units, i.e. 0.1 t ha h ha^{-1} MJ^{-1} mm^{-1} (Foster et al., 1981) (Fig.6). The results of a non-parametric Wilcoxon signed-rank test confirmed that on average, the estimated soil erodibility was significantly greater than 0.1 t ha h ha^{-1} MJ^{-1} mm^{-1} ($p=8\times10^{-10}$).

The degree of overestimation is on average 0.3 (at least 3x overestimation) with a standard deviation of 0.186. In all, 11 (of the 16) studies that used the standard nomograph, 24 (out of 44) papers that used the nomograph approximation equation, three (out of four) that used the Sharpley and Williams (1990) equation, all 14 studies that had read their K factor values from tables with respect to texture class and OM content and 18 (of the 20) studies that did not clearly specify the methods used, had overestimated the soil erodibility to varying degrees (Fig. 6). The commonness of this error possibly suggests some lack of attention on the part of most users towards the original unit (t acre h 100-acre^{-1} ft^{-1} tonf^{-1} inch^{-1}) of the K factor estimators and/or possible overlooking of the fact that these values must be multiplied by 0.1317 to convert from the imperial to SI units, in which measurement system these studies have reported their K factor values.

While it is not intrinsically wrong to estimate and report soil erodibility in the US customary units of t acre h 100-acre^{-1} ft^{-1} tonf^{-1} inch^{-1}, users must be mindful that the R factor is also expressed in the same system of units, so that the eventually modelled soil losses would be assigned the unit of t acre^{-1} yr^{-1}. However, as most of the studies have reported their rainfall erosivity in the popular SI units of MJ mm ha^{-1} h^{-1} yr^{-1}, the K factor must also be given in t ha h ha^{-1} MJ^{-1} mm^{-1}. Similarly, the appropriate K factor unit when the rainfall erosivity is in metric units (t-m cm ha^{-1} h^{-1} yr^{-1}) is t ha h ha^{-1} t-m^{-1} cm^{-1}.

4.3 Computations of the LS factor

The dimensionless topographic factor LS comprises of the slope length (L) and slope steepness (S) factors. Wischmeier and Smith (1978: page no. 14) defined L as “the distance from the point of origin of overland flow to the point where either the slope gradient (S) decreases enough that deposition begins, or the runoff water enters a well-defined channel that may be part of a drainage network or a constructed channel”. The L factor is basically the ratio of soil loss occurring from any slope relative to that from the USLE unit plot, raised to an exponent, the value of which was denoted as a function of the slope gradient in the USLE and as the ratio of the rill to interrill erosion in the RUSLE. While soil loss increases with increasing slope length (Wischmeier and Smith, 1978), the influence of slope steepness (whether constant or increasing) is far more pronounced (McCool et al., 1989). When the USLE was first proposed (Wischmeier and Smith, 1965), the S factor was devised as a quadratic function of the slope gradient taken as percent slope (Smith and Wischmeier, 1957), which upon upgradation, was replaced by another quadratic equation that models it as a function of the sine of the slope (Wischmeier and Smith, 1978). In the RUSLE, two different linear equations were proposed to estimate the S for slope gradients higher and lower than 9%, along with another equation that should be used to evaluate the S for slope lengths shorter than 4.5 m. The RUSLE also provides two similar equations (differently again as per the slope gradient being more or less than 9%) to estimate the S for thawing, weakened soils (McCool et al., 1989; Renard et al., 1997). A further equation based on a linear function relationship between the slope steepness factor and the sine of the slope angle was also devised by Nearing (1997) for slope gradients higher than 22%, which closely fits the RUSLE provided equations for slope gradients up to 22% and was also seen to be pertinently applicable for gradients higher than this value.

The LS factor could originally only be computed for uniform slopes (Wischmeier and Smith, 1965), but was soon extended to irregular slopes as well. However, irregular slopes must first be sub-divided into individual segments of uniform slope gradients that can then be considered uniform, with the LS factor values being calculated for each segment (Foster and Wischmeier, 1974; Wischmeier and Smith, 1978; Renard et al., 1997) or it can be computed by introducing a power equation describing the slope profile and modifying the RUSLE LS factor equations following the methodology of Di Stefano et al. (2000). Building on the development of a physically-based equivalent of the LS factor (Moore and Burch, 1986; Moore and Wilson, 1992), Desmet and Govers (1996) really facilitated LS factor computation for irregular slopes and complex topographies by proposing a novel method that applied flow accumulation algorithms on Digital Elevation Models (DEMs) in a GIS environment. Their solution was that the unit contributing area of each cell, calculated from the upslope drainage area, could substitute the slope length. As it is natural for surface runoff to converge and diverge over the landscape before ending in a 'well-defined channel', the LS factor calculated in this manner readily paved the way for large-scale USLE-based soil loss modelling that was hitherto impossible. Although the method of Desmet and Govers (1996) has been globally accepted (Benavidez et al., 2018), further advances have been made in the last few decades to further improve LS factor computations by applying different flow accumulation algorithms on DEMs (e.g. Winchell et al., 2008; Zhang et al., 2013, 2017). However, a further consideration should be the most apt flow routing algorithm (single or multi-directional) to be employed in a certain terrain, based upon which the flow accumulation surface is derived (Alewell et al., 2019).

Presently, the computation of the topographic factor is rather easy with multiple freely available DEMs to choose from, with a range of resolutions appropriate for catchment-scale to continent-scale applications. The problem with LS factor estimation is therefore not data unavailability but rather the improper usage of the LS factor equations while using DEMs. For example, most open-source global DEMs (i.e. datasets other than LiDAR generated elevation grids) are unable to capture the minute and concentrated flow paths/channels that mark the end of a USLE/RUSLE slope segment due to their relatively coarse spatial resolution and consequently the computed slope lengths are too long in most cases. Therefore, in order to prevent such an overestimation, the slope lengths are simply cut off at some arbitrary value– a decision that rests with the researcher and hence subjectivity cannot be ruled out (Renard et al., 2011). It is therefore more prudent to threshold slope lengths at 122 m, which not only corresponds to the maximum length of the USLE soil loss plots but also equals the most frequently observed slope lengths in the field (McCool et al., 1989; Renard et al., 1997).

Table 3: Summary of the various methods employed to quantify LS factor for USLE-based soil erosion modelling in India

Code in Fig. 4	Source	Equation	No. of studies used	Details of usage in reviewed applications
LS1	Smith and Wischmeier (1957)	$\boldsymbol{LS = (\frac{\lambda}{22.13})^{m} \times (0.065 + 0.045s + 0.0065s^2)}$ λ: slope length (m); s: slope gradient (%) m: varies between 0.2 and 0.5 depending on the slope gradient	14	λ estimated using: flow accumulation (n=8); set constant (n=2) equation $\lambda = 158 - 2.92s$ (n=1); no details (n=3) s obtained from: topographical maps (n=7); DEM (n=5); field measurements (n=1); no details (n=1)
LS2	Wischmeier and Smith (1978)	$\boldsymbol{LS = (\frac{\lambda}{22.13})^{m} \times (65.41\ \sin^2\theta + 4.56\sin\theta + 0.065)}$ λ: slope length (m); θ: slope angle m: dependent on the slope gradient – 0.5 if slope ≥ 5% – 0.4 if slope is between 3.5% and 4.5% – 0.3 if slope is between 1% and 3% – 0.2 if slope ≤1%	21	λ estimated using: flow accumulation (n=4); field measurements (n=1) equation $\lambda = 40 + 0.4s$ (n=4); set constant (n=2); no details (n=10) θ obtained from: topographical maps (n=5), field measurements (n=1), DEM (n= 10), no details (n=5)

LS3	Moore and Burch (1986), Desmet and Govers (1996)	$\boldsymbol{LS = (\frac{As}{22.13})^{0.4} \times (\frac{\sin\theta}{0.0896})^{1.3}}$ As: unit contributing area; θ: slope angle As = flow accumulation × DEM cell size	24	θ obtained from DEM (n=18) and topographical maps (n=6)
LS4	Moore and Wilson (1992), Desmet and Govers (1996)	$\boldsymbol{LS = (\frac{As}{22.13})^{m} \times (\frac{\sin\theta}{0.0896})^{1.3}}$ As: unit contributing area; θ: slope angle m = 0.4 – 0.6 As = flow accumulation × DEM cell size	10	θ obtained from DEM (n=8) and topographical maps (n=2)
LS5	McCool et al. (1989)	$\boldsymbol{L = (\frac{\lambda}{22.13})^{m}}$ $\boldsymbol{m = \frac{\beta}{1+\beta}}$ $\boldsymbol{\beta = \frac{(\frac{\sin\theta}{0.0896})}{3\,(\sin\theta)^{0.8} + 0.56}}$ $\boldsymbol{S = 10.8\sin\theta + 0.03}$ **(For slopes <9%)** $\boldsymbol{S = 16.8\sin\theta - 0.5}$ **(For slopes ≥9%)** $\boldsymbol{S = 3\,(\sin\theta)^{0.8} + 0.56}$ **(For λ <4.5 m)** λ: slope length (m); θ: slope angle	26	λ estimated using: flow accumulation (n=15), set constant (n=4) no details (n=7) θ obtained from: topographical maps (n=6), DEM (n= 20)
LS6	Smith and Wischmeier (1957), Wischmeier and Smith (1978), McCool et al. (1989)	**Comparison of various LS factor methods**	1	
LX		Method unclear	4	N/A

In all, 64 of the 100 studies examined here had used a DEM to compute the LS factor. The ASTER GDEM and SRTM DEM were the most popularly used DEM datasets, even though this choice of DEM or DEM resolution appears to be arbitrary in all cases despite the fact that the ascertained topographic parameters from each DEM can vary markedly (Das et al., 2016). Of the remaining examples, 28 studies had estimated the LS factor for their study area from topographical maps (either manually or from contour-generated DEMs), one plot-scale study had actually measured the LS factor in the field while the rest did not mention any data source. The LS factor estimation methods are detailed in Table 3.

In total, 34 studies had applied the equations developed by Moore and Burch (1986) and Moore and Wilson (1992), which are based on the concept of unit stream power. All of these 34 studies estimated the L factor from a flow accumulation surface as suggested by Desmet and Govers (1996). Although Wischmeier and Smith (1978) had replaced the earlier LS factor equation of Smith and Wischmeier (1957) with a more pertinent equation that models S values as a quadratic function of the sine of the slope angle, the latter (i.e. older equation) was still used in 14 of the studies reviewed. Just 22 studies employed the updated equation of Wischmeier and Smith (1978), four of which specified an unrealistic value of 0.7 (which exceeds the maximum possible value of 0.5) for the exponent *m*. In all, 26 studies had calculated the LS factor as per the RUSLE method (Renard et al., 1997), though only four had actually obtained the m exponent of the L factor through estimation of the rill to interrill erosion ratio as should be done for RUSLE. We observed that in nine cases, the slope length (λ) was taken to be the same as the DEM resolution, which varies between 23.5 m and 200 m. The justification of such an assumption was unclear in all cases, but according to our understanding, a constant slope length could result in considerable under- or overestimation of the LS factor and consequently a similar aberration in the estimated soil loss rates.

Another issue that leads to overestimation of soil loss rates stems from users considering abnormally long slope lengths (Renard et al., 2011). Thus it is especially important for modellers using a DEM and flow accumulation algorithms to calculate the L factor to apply an appropriate channel initiation threshold to truncate the overland flow paths as they terminate in a 'well-defined channel' (Haregeweyn et al., 2017; Almaw Fenta et al., 2019). Of the 61 studies that used a flow accumulation surface to calculate slope lengths, only three explicitly mentioned how the flow accumulation raster was thresholded. There was no objective means to assess if and how the remaining 58 studies obtained the slope lengths from their respective flow accumulation rasters. Five studies even calculated slope lengths using regression equations ($\lambda = 40 + 0.4s$; $\lambda = 158 - 2.92s$) that were functions of the slope steepness, though no sources were cited for these equations and 24 other studies supplied no information on the LS factor estimation apart from the equation used. In sum, many questions remain concerning the LS factor estimation (both in terms of ascertained values and clarity of method) in the bulk of USLE applications in India.

4.4 Computations of the C factor

The cover and management factor is defined as the ratio of soil loss from a field with specific cover and management to that of a field under 'clean-tilled continuous fallow' (Wischmeier and Smith, 1965, 1978). Being a ratio, it normally varies between 0 and 1.0, unless an area is more erosion-prone than the unit-plot (Karpilo and Toy, 2003; Renard et al., 2011) It is one of the most important USLE factors because it represents the most readily manageable condition for reducing erosion (Wischmeier and Smith, 1978; Renard et al., 1997).

The USLE C factor estimation procedure differs between land cover/use classes. For croplands, it is estimated annually by considering soil loss ratios and relative rainfall erosivities for different crop growth stages. Therefore the C factor represents how the crop calendar and agricultural practices influence soil erosion in a region. For various non-agricultural land uses such as pastures, rangelands and undisturbed forests or woodlands, the estimation scheme is somewhat different in that it varies as a function of the vegetation height, canopy and ground cover (undergrowth, litter and other such aspects). The USLE also allows C factor estimation for construction sites (Wischmeier and Smith, 1965, 1978).

The RUSLE C factor probably underwent the most significant change among all the factors compared to that of the USLE, as a subfactor-based approach was devised to evaluate C values for all types of land cover/use classes. Soil loss ratios were not to be estimated anymore from tables but to be calculated as a product of the prior-land-use (PLU), canopy-cover (CC), surface-cover (SC), surface-roughness (SR) and soil-moisture (SM), for each time period over which these sub-factors can be assumed to be constant. Subsequently, each of the soil loss ratio values are weighted by the fraction of (relative) rainfall erosivity of the corresponding time period and then combined into an overall C factor value (Renard et al., 1997).

The problem with estimating the C factor either according the textbook USLE or RUSLE approach is that they require voluminous data on the spatio-temporal dynamics of land cover/use of the examined area, in addition to knowledge of local agricultural practices (Gabriels et al., 2003), which is often impracticable to monitor directly or impossible to gain otherwise, especially at the catchment- or regional-scale. Consequently, the process of C factor estimation has undergone considerable simplification and cover-specific values are simply obtained from existing literature and applied to land cover/use maps (Benavidez et al., 2018; Alewell et al., 2019). As an alternative to the original USLE/RUSLE methods or the look up table based approach of estimating the C factor, the use of remotely sensed imagery and various image derived band ratios or indices have gained traction (De Jong, 1994; Van der Knijff et al., 2000; Schönbrodt et al., 2010; Zhang et al., 2011; Panagos et al., 2015a; Teng et al., 2016; Schmidt et al., 2018). However, though remote sensing helps to estimate time-varying C factors and facilitates sub-annual or seasonal soil erosion prediction, it fails to adequately capture or properly represent the inherent management aspect of this component (Alewell et al., 2019).

Proper assessment of the C factor estimation methods as adopted in the reviewed studies was the most difficult to accomplish. This is because catchment-scale USLE applications do not normally follow the methodology suggested by Wischmeier and Smith (1978) or Renard et al. (1997), due to the obvious reasons outlined above. Of the reviewed studies, only the plot-scale study of Ali and Sharda (2005) obtained the C factor values as per the USLE methodology. Alewell et al. (2019) noticed that in most USLE applications, C factor values are simply obtained from the literature. This certainly holds true for India, with 56 studies clearly having done the same (Table 4). However, some studies did not explicitly state a source and in most cases the denoted/used C factor values corresponding to different land cover/use types were obtained from different sources, without consideration of the fact that the land use as well as definitions of land cover may vary in the examined area compared to the region from where these values were originally estimated.

None of the reviewed applications considered crop rotation while estimating the C factor values for croplands. In 16 studies, croplands were assigned higher C values than degraded barren areas or wastelands, implying a higher soil loss susceptibility of croplands, which is rather counterintuitive and unlikely to find ratification in the available literature. A Normalised Difference Vegetation Index (NDVI)-based approach to C factor estimation was adopted in 31 studies, 27 of which employed the equation coined by Van der Knijff et al. (2000) and four used a simple regression equation that estimates the C factor as a function of the NDVI (Patil and Sharma, 2013). Although one advantage of using the NDVI parameter is its potentiality of determining C factors sub-annually, upon availability of cloud-free imagery, the equation proposed by Van der Knijff et al. (2000) has been observed to produce unrealistically high C factor values in non-agricultural areas (Benavidez et al., 2018). It was not clear how the studies that employed this method tackled the problem of C factor overestimation in non-agricultural areas but 10 of them had C factor values greater than 1, which is quite unrealistic. Three of the four studies that used the regression equation of Patil and Sharma (2013) also overestimated the C factor. Generally speaking, it seems as if the C factor estimation in most cases has been based on the user's arbitrary decisions, rather than scientific objectivity, which is not unheard of when it comes to estimation of both the C and P factors

(Karpilo and Toy, 2003). However, with the C factor being so important in predicting soil loss rates and also in demonstrating the possible efficacies of any implementable ameliorative measures, any such miscalculation directly deteriorates the accuracy of modelled erosion rates.

Table 4: Summary of the various methods employed to estimate the C factor for USLE-based soil erosion modelling in India

Code in Fig. 4	Method	No. of studies
C1	As per USLE (Wischmeier and Smith, 1978)	1
C2	Values from literature corresponding to land cover/use classes	56
C3	$C = exp\left[\alpha(\frac{NDVI}{\beta - NDVI})\right]$ where $\alpha = 2$; $\beta = 1$ (Van der Knijff et al., 2000)	27
C4	$C = 1.02 - 1.21\ NDVI$ (Patil and Sharma, 2013)	4
CX	Unclear	12

4.5 Computations of the P factor

The support practice (P) factor is "the ratio of soil loss with a specific support practice to the corresponding loss with up-and-down-slope culture" (Wischmeier and Smith, 1978: page no. 14). It is representative of the efficacy of erosion control measures, with values close to zero suggestive of the success of a particular erosion control practice. Contouring, contour stripcropping, terracing and stabilised waterways are some of the conservation practices recommended to reduce the P factor value of a cropland (Wischmeier and Smith, 1965, 1978). The USLE guidebook of Wischmeier and Smith (1978) contains detailed tables to estimate the P factor value for each of the mentioned practices as a function of the slope gradient and length, which can be reliably used to evaluate the P factor for croplands.

As for the other factors, P factor estimation methods were upgraded in the RUSLE and a larger range of support practices incorporated, owing to the CREAMS (Chemicals, Runoff, and Erosion from Agricultural Management Systems) model based analytical experiments and availability of more experimental data (Renard et al., 1997, 2011). Akin to the C factor, the RUSLE P factor is calculated as a product of sub-factors for individual support practices that are normally combined to achieve the best possible erosion control. However, the original USLE or RUSLE method is rarely followed to obtain P factor values while modelling soil erosion at the catchment- or regional-scale (Alewell et al., 2019), and for non-agricultural land uses, the P factor definition is confusing and also somewhat misleading. Karpilo and Toy (2003) have discussed this problem further and mentioned that the majority of non-agricultural RUSLE applications assume the absence of any conservation practice and specify the P value to be 1.0. For the majority of non-agricultural land uses, such as forests, woodlands, grasslands or urban areas, this seems to be appropriate if no special operation or activity is undertaken to arrest or divert runoff and promote deposition.

Evaluation of the P factor estimation methods used in the reviewed papers proved to be just as difficult as that for the C factor. 24 studies had considered the P factor to be constant at 1.0 (Table 5), which is appropriate if no erosion control measures exist (Karpilo and Toy, 2003; Benavidez et al., 2018). 17 studies had assigned two P factor values, i.e. 0.28 for croplands and 1.0 for the rest of their study area following Rao (1981). Due to the inaccessibility of this paper, it is unclear on which basis (i.e. kind of existing support practice) the P value for croplands was assigned as 0.28 and further if this study had considered a range of agricultural practices or not. 22 studies had obtained P values specific to certain land cover/use classes but 18 of these did not provide any source. Finally, seven studies had used one of the tables provided by Wischmeier and Smith (1978) on P factor values for croplands under contouring, but none of them had also provided any information on how values were estimated for non-agricultural areas and whether the agricultural lands in their respective study areas were indeed all under contouring-based management. 30% of the reviewed studies did not clearly state or provide any details on their method of P factor estimation.

Table 5: Summary of the various methods employed to estimate the P factor for USLE-based soil erosion modelling in India

Code in Fig. 4	**Method**	**No. of studies**
P1	Values from literature corresponding to land cover/use classes	22
P2	P factor for contouring (Wischmeier and Smith, 1978)	7
P3	P=1 assigned due to absence of any support practice	24
P4	Assigned P=0.28 for croplands and P=1 for non-croplands as per Rao (1981)	17
PX	Unclear	30

4.6 In a nutshell

Over half (55%) of the studies we reviewed claimed that they had used the RUSLE framework to estimate soil erosion, which was strictly speaking, not the case as per their adopted methodology. This confusion over the correct nomenclature is mainly caused by the identical equations of the USLE and the RUSLE. The RUSLE is difficult, if not impossible to use, for large-scale soil erosion modelling in general and even more so in data-sparse conditions of India, as it necessitates parameterisation in sub-annual timescales. All the studies had directly or indirectly followed the USLE method for R and K factor estimation and such misnomers in terms of the model use possibly further highlight a deficient understanding/adoption of the correct model parameters, units and computation methods.

Viable estimations of the C and P factors are the main impediment in the way of large-scale USLE applications. Even though the C factor is rarely, if at all, computed following the USLE methodology in contemporary studies, the common practice of obtaining C factor values corresponding to land cover/use classes from previous studies is inherently a USLE-based approach, since these C factor values were originally estimated following the USLE methodology (see Morgan (2005) for an example). The use of arbitrary C and P factor values (i.e. eliciting them from studies conducted in areas quite different to the location being examined) thus presents a real challenge. Possibly, this can be surmounted to an extent using the high resolution satellite images (that are also multi-temporal and multi-spectral) and terrain datasets that are progressively becoming more available.

Nonetheless, all factors considered together, the vast majority of papers sampled here misapplied the USLE while modelling soil erosion in various parts of India. We observed that lack of attention towards factor estimation methods, their units or their applicability in India was surprisingly ubiquitous. Most of the studies estimated rainfall erosivity using an erroneous or ill-suited equation and/or reported their values in the wrong units, causing a gross underestimation of the same. Use of short-term rainfall data of only a few years was also observed to result in considerable inaccuracies even when the rainfall erosivity was measured as per the guidelines of the Agricultural Handbook No. 537 (Wischmeier and Smith, 1978). The clear overvaluation of the K factor, on the other hand, is probably solely due to the various users' lack of attention towards denoting the appropriate units (with respect to the R factor) and its maximum possible value. Furthermore, it is worth noting that most studies have homogenised the K factor values over regions larger than what is deemed suitable as per its spatial variability limits and thus have feasibly missed out on adequately capturing the inherent variability in soil erodibility within the examined areas (i.e. thereby possibly over- or underestimating this parameter). While substantial doubts also remain about the undertaken LS factor computations in general, the estimation of the C and P factors in an overwhelming majority of publications from India are quite inaccurate, inconsistent and possibly bereft of sound foundations. Since both these factors are given as ratios, assigning arbitrary values could certainly culminate in a severe miscalculation of soil loss rates or abet impaired/skewed judgements about erosion mitigation measures.

The fact that a large number of studies did not supply enough (if any) information on one or more of their factor estimation procedures stymied our evaluations as well. Of the 100 papers examined, the field-scale study of Ali and Sharda (2005) that sought to assess the applicability of the USLE in India stood out in terms of technical clarity and viability of findings. They used the USLE to simulate soil erosion at the most appropriate scale (i.e. plot- to field-scale) and found that the coefficient of determination between the measured and simulated soil loss values was between 0.88 and 0.91, with no statistically significant difference existing between the observed and simulated values at the 1% alpha-level. Among the studies that aimed to simulate soil erosion at larger spatial scales, Nagaraju et al. (2011), Nakil and Khire (2015) and Swarnkar et al. (2018) stood out by virtue of their consistent and accurate factor estimation. Even though none of these three studies attempted to validate their model output, Swarnkar et al. (2018) proposed a framework to assess the model uncertainty, which is relevant when the USLE is used in large, ungauged river basins. Since only a paltry four of the 100 studies we reviewed were observed to have applied the USLE correctly, there is definitely room for and an urgent need to markedly improve future USLE applications in India.

5. A roadmap for future USLE applications in India

Presently, with the considerable amount of open-source data available to apply the USLE at the sub-continental, continental or global scales, many studies have been undertaken in this regard (e.g. Borrelli et al., 2017; Panagos et al., 2018; Almaw Fenta et al., 2019; Koirala et al., 2019; Borrelli et al., 2020; Panagos et al., 2020). However, USLE applications in field-settings or catchments cannot benefit much from these data due to their coarse resolution and the associated uncertainty at these scales. Careful curation of the input data at an appropriately high resolution is thus necessary (cf. Borrelli et al. (2014) and Swerts et al. (2019) for examples). In countries such as India where all the requisite data are not available or readily accessible, using the USLE for estimating soil erosion in catchments and river basins remains a challenge. Furthermore, the previous sections have highlighted the multiple erroneous estimations of the different USLE components in studies conducted herein and the concomitant skewed soil loss predictions. Addressing this, in the following sections we suggest the most appropriate combination of model parameterisation methods for Indian conditions, giving due consideration to data availability as well as demonstrate the best possible evaluation methods for each of the USLE's parameters, so as to contribute towards improving future USLE applications in India.

5.1 Correctly computing the R factor

To date, the most appropriate and accurate estimator of the rainfall erosivity factor in India is the method adopted by Babu et al. (2004). They analysed long-term data of monthly, seasonal and annual rainfall erosivity for 123 stations across India and framed two linear regression equations to estimate the annual and seasonal (June–September, i.e. the summer monsoon period) erosivity separately, by using annual and monsoonal rainfall, respectively. Both equations had high correlation ($r \geq 0.9$) between erosivity and rainfall amounts. As mentioned before, these equations estimate the R factor in metric units of t-m cm ha^{-1} h^{-1} yr^{-1}, which is converted to MJ mm ha^{-1} h^{-1} yr^{-1} by a multiplication factor of 10.2 as shown below.

$$1\left[\frac{\text{t}-\text{m cm}}{\text{ha h yr}}\right]=\left[\frac{9806.65\text{ Nm cm}}{\text{ha h yr}}\right]=\left[\frac{98066.5\text{ Nm mm}}{\text{ha h yr}}\right]=\left[\frac{98066.5\text{ J mm}}{\text{ha h yr}}\right]=0.098\left[\frac{\text{MJ mm}}{\text{ha h yr}}\right]$$

Therefore, $1\left[\frac{\text{MJ mm}}{\text{ha h yr}}\right]=10.204\left[\frac{\text{t}-\text{m cm}}{\text{ha h yr}}\right]$

Therefore the equations of Babu et al. (2004) can be rewritten as –

$$R_a = 831.626 + 3.877P_a \qquad \text{(Eq. 3)}$$

$$R_s = 733.668 + 3.684P_s \qquad \text{(Eq. 4)}$$

where, R_a and R_s are the annual and seasonal rainfall erosivity, in units of MJ mm ha^{-1} h^{-1} yr^{-1}, calculated from annual rainfall (P_a) and seasonal rainfall (P_s), respectively. As hitherto mentioned, annual/monthly/ seasonal precipitation must always be averaged over decadal timescales before computing the R factor using any suitable regression equation.

The requisite rainfall data (both spatial and non-spatial) can be obtained from the India Meteorological Department (IMD) website (https://imdpune.gov.in/index.html). IMD data are based on long-term gauge records and can be used reliably. However, the interpolation method used must be clearly specified if gauge data is used. The WorldClim data repository (https://www.worldclim.org/) also provides gauge-based data in a gridded format, which can be used as well. Since Babu et al. (2004) developed their equations using measured rainfall data, the use of satellite-based rainfall products such as the Tropical Rainfall Measurement Mission (TRMM) or model-derived data like CFSR (Climate Forecast System Reanalysis) is not recommended, unless these have been extensively evaluated against the measured rainfall records in the intended study area.

5.2 Correctly computing the K factor

The soil erodibility calculated from runoff plots per unit of rainfall erosivity index in various parts of the country corresponded best with the nomograph-derived K factor values and hence use of the nomograph is recommended (Singh et al., 1985). However, data availability/accessibility issues do arise during soil erodibility estimation in India. Although soil maps of some states can be obtained from the data portal of the European Soil Data Centre (https://esdac.jrc.ec.europa.eu/), these are not accompanied by corresponding soil survey reports or analytical data, even though the scale (1:500000) of state-level soil maps is adequate for soil erodibility mapping for USLE applications at the catchment scale and beyond. The National Bureau of Soil Survey and Land Use Planning (NBSS&LUP), the nodal soil survey organisation in India, has not yet made their maps and survey reports available openly either. Since for basin-scale soil erosion modelling, estimating the soil erodibility from collected soil samples is not feasible owing to the expenses and logistics involved, gridded soil databases perforce have to be used. The most popular gridded soil database is the International Soil Reference and Information Centre (ISRIC) SoilGrids (https://soilgrids.org/), which provides depth-wise rasterised data on a number of soil physico-chemical properties as well as the most probable soil classifications at a resolution of 250 m (Hengl et al., 2017).

However, a few points are noteworthy while using the ISRIC SoilGrids data to estimate soil erodibility. Primarily, all the requisite data (sand, silt, clay and organic carbon content) must be converted to percent contents. The very fine sand (0.05–0.1 mm) content is usually not measured in standard soil textural analysis and data on this fraction is not available from ISRIC. It can however be taken as 20% of the sand content (0.05–2.0 mm) for soil erodibility estimation (Panagos et al., 2014). ISRIC only provides data on organic carbon content, which must be converted to organic matter content by multiplying the obtained figures with the Van Bemmelen factor of 1.724 (Heaton et al., 2016). Since soil structure or permeability data is not available from the ISRIC, these have to be indirectly estimated with respect to the major texture classes (Table 6, Table 7).

Table 6: Soil structure types inferred from major soil textural classes as per Bagarello et al. (2009)

Soil texture	Structure types
Sand, loamy sand, sandy loam	1 (very fine granular)
Sandy clay, sandy clay loam, loam, silty loam, silt	2 (fine granular)
Clay loam, silty clay loam	3 (medium or coarse granular)
Silty clay, clay	4 (blocky, platy or massive)

Table 7: Soil permeability classes estimated from major soil textural classes as per Rawls et al. (1982)

Soil texture	Permeability class
Sand	1 (fast and very fast)
Loamy sand, sandy loam	2 (moderately fast)
Loam, silty loam, silt	3 (moderate)
Sandy clay loam, clay loam	4 (moderately slow)
Silty clay loam, sandy clay	5 (slow)
Silty clay, clay	6 (very slow)

Graphical estimation of the soil erodibility using the nomograph is not possible when gridded soil datasets are used and the approximation equation (Code K3 in Table 2) cannot be used for the available range of soil properties. Consequently, soils with silt and very fine sand content exceeding 70% or having OM content greater than 4% are often excluded from large-scale soil erodibility mapping or scaled down to 70% silt and very fine sand and 4% OM (Panagos et al., 2014; Borrelli et al., 2017; Almaw Fenta et al., 2019). However, it is for such situations that the K factor estimation method developed by Auerswald et al. (2014) is most useful. This method enables K factor estimation in four steps, though in situations where data on surface coarse fragments cover is not available (such as when using the ISRIC SoilGrids data) or when a correction for coarse fragments need not be applied, the computation terminates after the third step.

Step 1:

$$K_1 = 2.77 \times 10^{-5} \times (f_{Si+vfSa} \times (100 - f_{Cl}))^{1.14} \qquad \text{(for } f_{Si+vfSa} < 70\%\text{)} \qquad \text{(Eq. 5)}$$

$$K_1 = 1.75 \times 10^{-5} \times \left(f_{Si+vfSa} \times (100 - f_{Cl})\right)^{1.14} + (0.0024 \times f_{Si+vfSa}) + 0.16$$

$$\text{(for } f_{Si+vfSa} > 70\%\text{)} \qquad \text{(Eq. 6)}$$

Step 2:

$$K_2 = \frac{(12 - f_{OM})}{10} \qquad \text{(for } f_{OM} < 4\%\text{);} \qquad \text{(Eq. 7)}$$

$$K_2 = 0.8 \qquad \text{(for } f_{OM} > 4\%\text{)} \qquad \text{(Eq. 8)}$$

Step 3:

$$K_3 = K_1 \times K_2 + 0.043 \times (A - 2) + 0.033 \times (P - 3) \qquad \text{(for } (K_1 \times K_2) > 0.2\text{)} \qquad \text{(Eq. 9)}$$

$$K_3 = 0.091 - (0.34 \times K_1 \times K_2) + 1.79 \times (K_1 \times K_2)^2 + 0.24 \times K_1 \times K_2 \times A + 0.033 \times (P - 3)$$

$$\text{(for } (K_1 \times K_2) < 0.2\text{)} \qquad \text{(Eq. 10)}$$

Step 4:

$$K = K_3 \qquad \text{(for } f_{rf} < 1.5\%\text{)} \qquad \text{(Eq. 11)}$$

$$K = K_3 \times (1.1 \times \exp\left(-0.024 \times f_{rf}\right) - 0.06) \qquad \text{(for } f_{rf} > 1.5\%\text{)} \qquad \text{(Eq. 12)}$$

where, K is the soil erodibility expressed in t ha^{-1} h N^{-1}, $f_{Si+vfSa}$ is silt and very fine sand (2–100 μm) mass fraction (%), f_{Cl} is mass fraction (%) of clay (<2 μm), f_{OM} is organic matter mass fraction (%) in the fine earth (<2 mm) fraction, and f_{rf} is the fraction of the soil surface covered with rock fragments. A is the soil structure index: very fine granular = 1; fine granular = 2; medium or coarse granular = 3; and blocky, platy, or massive = 4; and P is soil permeability index: very fast = 1, moderate fast = 2, moderate = 3, moderate slow = 4, slow = 5, and very slow = 6. The conversion from t ha^{-1} h N^{-1} to t ha h ha^{-1} MJ^{-1} mm^{-1} is done by dividing the ascertained K factor values by 10.

5.3 Correctly computing the LS factor

In India, the SRTM DEM of 30 m resolution has so far been found to be the most accurate of all freely available gridded elevation datasets for soil erosion modelling (Mondal et al., 2016b, 2017; Saxena et al., 2020). The RUSLE method of LS factor estimation (McCool et al., 1989; Renard et al., 1997) represents an improvement over the equations of Smith and Wischmeier (1957) or Wischmeier and Smith (1978) in all directions and its use is recommended (Renard et al., 1997, 2011). A further equation based on a linear function relationship between the slope steepness factor and the sine of the slope angle was also devised by Nearing (1997) for slope gradients higher than 22%, which closely fits the RUSLE provided equations for slope gradients up to 22% and was also seen to be pertinently applicable for gradients higher than this value and can feasibly be used. However, while using one of the popular open-source DEMs available so far (ASTER GDEM, SRTM DEM, JAXA AW3D, Copernicus DEM, CartoDEM, ALOS PALSAR DEM), the RUSLE LS factor for short slopes ($\lambda < 4.5$ m) cannot be calculated, since their respective pixel size exceeds 4.5 m (as high resolution LiDAR data is still freely not available for almost the entirety of India).

For the most accurate calculation of the LS factor, it is necessary to truncate the slope lengths as they reach a channel and not consider slope gradients above 60% (Wischmeier and Smith, 1978; Renard et al., 1997). In order to estimate a suitable channel initiation threshold for the purpose of truncating slope lengths, one can make use of the high-resolution imagery available in Google Earth or OpenStreetMap, to identify channel initiating points. The same can also be done with the aid of topographical maps (e.g. Jain and Das, 2010), or by using information from other studies in the same region (e.g. Haregeweyn et al., 2017). Once channel initiation points are identified, the flow accumulation value up to these points (to be taken from the flow accumulation grid pixel within which the point is situated) needs to be considered while excluding any other grids of higher flow accumulation values. Finally, slope lengths must be shorter than or equal to 122 m, as this corresponds to the maximum length of USLE soil loss plots, as well as the most frequently observed field slope lengths (McCool et al., 1989; Renard et al., 1997).

5.4 Correctly computing the C factor

For large-scale C factor mapping, a land cover and land use (LULC) map is indispensable. We recommend using the LULC datasets available from the Bhuvan Geo-portal (https://bhuvan.nrsc.gov.in/), which can be loaded as a WMS layer in QGIS and subsequently saved as GeoTIFF files. It must be noted that layers saved in this manner cannot readily be analysed as they are simply georeferenced images. A convenient and fast intermediate step to get them ready for processing is to perform unsupervised classification. Since the various LULC types are already assigned different colours in the source image, an unsupervised classification perfectly discriminates between the various LULC classes and yields an analysis-ready chorochromatic layer. The LULC maps made available in the Bhuvan Geo-portal by the National Remote Sensing Centre (NRSC), India are products of supervised image classification and on-screen digitisation of Resourcesat-2 LISS-III 23.5 m resolution imagery. Three sets of maps are available at a scale of 1:50000, corresponding to LULC conditions of 2005-06, 2011-12 and 2015-16 respectively. The data are classified into 24 end-classes that are grouped into eight first-order LULC categories, viz. built-up, agriculture, forest, grassland, barren, rann (marsh), water and snow. The overall accuracy of these different LULC classes varies from 79% (agricultural plantation) to 97% (water) (NRSC, 2019a).

The best approach for C factor estimation is to follow separate procedures for croplands and non-croplands (Panagos et al., 2015a; Borrelli et al., 2017; Almaw Fenta et al., 2019), even though all C factor values are obtained from the literature. This is because C factor values for croplands vary between regions according to cropping characteristics (crop types, rotation, tillage and management) and are calculated as a weighted average, while the procedure is different for non-arable land cover classes.

5.4.1 Computing the C factor for croplands

In the Indian LULC classification system (NRSC, 2019a), the agriculture class is subdivided into croplands, agricultural plantation, current shifting cultivation and fallow. This subsection elaborates the method of C factor computation for croplands only.

Panagos et al. (2015a) calculated the C factor for croplands ($C_{croplands}$) in the European Union as:

$$C_{croplands} = C_{crop} \times C_{management} \qquad \text{(Eq. 13)}$$

where, C_{crop} is a weighted average value calculated as a summed product of the respective C factor of different crops and their acreage share in a region and $C_{management}$ adjusts the C factor value as a function of recognised management practices (e.g. tillage, cover crop and crop residues) that contribute towards reducing soil erosion.

Adapting this scheme to India, we propose computing the $C_{croplands}$ for each district as follows:

$$C_{croplands} = \sum_{i=1}^{15}(C_{cropi} \times \%DGCA_{cropi}) \times C_{tillage} \qquad \text{(Eq. 14)}$$

where, C_{cropi} is the C factor value of the ith crop (Table 8), $\%DGCA_{cropi}$ is the share of this crop in the district gross cropped area and the term $C_{tillage}$ corrects the C factor according to the tillage practice.

The gross cropped area represents the total area sown once and/or more than once in a particular year, i.e. the area is counted as many times as there are sowings in a year. Therefore the C factor value weighted against the share of a particular crop acreage in the district gross cropped area ($\%DGCA_{cropi}$) implicitly considers crop rotation within a year and thereby yields an annual C factor value. The requisite spatial and non-spatial data on the district crop acreage can be freely downloaded from the ICRISAT data portal (http://data.icrisat.org/) or obtained from state statistical handbooks. In India, conventional tillage is practised over most of the country, while reduced/zero tillage is done in the Indo-Gangetic plain (Gupta and Abrol, 1992; Bhan and Behera, 2014), for which the C factor corrections of 1 and 0.3 can be applied as per the scheme of Stone and Hilborn (2000). Since intensive agriculture is practised in India with multiple crop rotations in a year, cover crops are not usually planted and most of the crop residue is used as fodder or fuel or for preparing bio-fertilisers while the remnant stubble is often burnt in the field (DAC, 2014). Therefore, corrections for cover crops or crop residues need not be applied to the crop-specific C factor values. Table 8 contains the C factor values per crop type as estimated from experimental studies conducted solely in the tropics (Roose, 1977; Singh et al., 1981; El-Swaify et al., 1982; Hurni, 1985; Singh et al., 1985; David, 1988; Clay and Lewis, 1990; Singh et al., 1991; Nill et al., 1996), although data generated from India (Singh et al., 1981, 1985, 1991) has been preferred wherever applicable.

Table 8: C factor values from the literature for major crops (excluding plantation crops) grown in India

i	Crop type	Share (%) of country's gross cropped area (DES, 2017)	C factor
1	Rice	22.3	0.28
2	Wheat	16.2	0.3
3	Sorghum	3.1	0.63
4	Millets	4.9	0.61
5	Maize	4.4	0.42
6	Barley	0.4	0.3
7	Pulses	10.9	0.41
8	Oilseeds	14.3	0.4
10	Sugarcane	2.8	0.2
11	Cotton	6.4	0.55
12	Potatoes	1.05	0.4
13	Onion	0.65	0.4
14	Vegetables	3.3	0.3
15	Fodder	4.6	0.13

Note: Crop type Millets includes both pearl and finger millets, Pulses includes chickpeas, pigeonpeas and other pulses, and Oilseeds includes groundnut, sesame, soya, rapeseed, mustard, safflower, castor, linseed and sunflower.

5.4.2 Computing the C factor for non-croplands

While a literature review yielded singular C factor values for most of the non-cropland LULC classes (Table 10) that can directly be assigned, classes characterised by varying degrees of vegetal cover (Table 9) naturally have C factor values that differ according to the cover/use type (Panagos et al., 2015a; Borrelli et al., 2016). The assignment of unique C factor values is thus inappropriate for the latter category, as the combined effect of cover type and vegetation density must be captured. Enabling this, the following equation (Panagos et al., 2015a) calculates the C factor ($C_{noncropi}$) as a product of the range of class-specific C factor values and fractional vegetation cover:

$$C_{noncropi} = Min_C + (Max_C - Min_C) \times (1 - F_{cover}) \qquad \text{(Eq. 15)}$$

where, $C_{noncropi}$ is the calculated C factor value of the ith non-arable LULC class (Table 9), Min_C and Max_C are the minimum and maximum C-factor values corresponding to the LULC class (Table 9), and F_{cover} is the fractional vegetation cover (ranging from 0 to 1).

Based on this approach, the C factor is highest when F_{cover} equals 0 (i.e. no vegetation cover or bare soil) and lowest when F_{cover} equals 1 (i.e. the soil surface is fully covered by vegetation). Annual fractional vegetation cover data (F_{cover}) for various land cover types, derived from PROBA-V imagery, are available at 100 m resolution from the Copernicus Global Land Cover viewer (https://lcviewer.vito.be/) and can be used to quantify the effects of vegetal cover on C factor estimation for non-arable areas.

Table 9: C factor values from the literature for non-cropland LULC classes (as per NRSC classification 2015-16) with varying vegetal cover

i	LULC class	Description	C factor values	Source
1	Agricultural Plantation	It includes agricultural plantation (e.g. tea, coffee, rubber etc.) horticultural plantation (e.g. coconut, arecanut, citrus fruits, orchards, fruits, ornamental shrubs and trees, vegetable gardens etc.) and agro-horticultural plantation.	0.1–0.3	David (1988), Antronico et al. (2005), Bakker et al. (2008), Borselli and Torri (2008); De Vente et al. (2009); Diodato et al. (2011)
2	Forest Plantation	Areas under tree species of forestry importance raised and managed especially in notified forest areas.	0.0001–0.003	Wischmeier and Smith (1978)
3	Evergreen/Semi-evergreen	Area under perennial plants that are never entirely without green foliage	0.0001–0.003	Wischmeier and Smith (1978)
4	Deciduous	Area under perennial plants that are leafless during the dry season	0.0001–0.003	Wischmeier and Smith (1978)
5	Scrub forest	Open forest areas generally seen at the fringes of dense forest cover and settlements	0.0001–0.003	Wischmeier and Smith (1978)
6	Swamp/Mangroves	Tropical and subtropical vegetation species that are densely colonised on coastal tidal flats, estuaries, salt marshes etc.	0.0001–0.003	Wischmeier and Smith (1978)
7	Grass	It includes natural/semi-natural grass/ grazing lands of Alpine/Sub-Alpine or temperate or sub-tropical or tropical zones, desertic areas and manmade grasslands.	0.003–0.45	Wischmeier and Smith (1978)
8	Salt-affected land	Land characterised by saline soils and sparse grass cover	0.003–0.45	Wischmeier and Smith (1978)
9	Scrubland	These areas possess shallow and skeletal soils, at times chemically degraded extremes of slopes, severely eroded or subjected to excessive aridity with scrubs dominating the landscape.	0.45–1.0	Wischmeier and Smith (1978), David (1988), Borselli and Torri (2008), Capolongo et al. (2008)

Table 10: C factor values from literature for the other non-cropland LULC classes (as per NRSC classification 2015-16) that can be assigned directly

LULC class	Description	C factor values	Source
Fallow	Lands adjacent to croplands with an alternation between a cropping period of several years and a fallow period.	0.45	Shi et al. (2004), Nyakatawa et al. (2007)
Current shifting cultivation	Lands adjacent to forests with an alternation between a cropping period of several years and a fallow period.	0.45	Shi et al. (2004), Nyakatawa et al. (2007)
Mining	Area under surface mining operations	1.00	Wischmeier and Smith (1978)
Gullies/ Ravines	Entrenched erosional feature formed by concentrated surface runoff	0.00	Wischmeier and Smith (1978)
Sandy area	Swathes of sand in coastal or inland areas	0.00	Panagos et al. (2015a)
Barren rocky	Rock exposures devoid of soil and vegetal cover	0.00	Panagos et al. (2015a)
Rann	An extensive salt marsh of western India between the Gulf of Kutch and the Indus River delta.	0.00	Panagos et al. (2015a)
Urban	Built up areas covered by impervious structures adjacent to or connected by streets.	0.00	Märker et al. (2008), Diodato et al. (2011)
Rural	Built-up areas, smaller in size than urban, mainly associated with agriculture and allied sectors and non-commercial activities.	0.00	Märker et al. (2008), Diodato et al. (2011)
Wetlands/ Water bodies	Includes inland and coastal wetlands, rivers, streams, canals, reservoir, lakes and ponds	0.00	Panagos et al. (2015a)
Snow and Glacier	Areas under perpetual snow/ice cover in the Himalayas	0.00	Panagos et al. (2015a)

5.5 Correctly computing the P factor

Panagos et al. (2015b) have devised a P factor map for the European Union by using field-surveyed information. However, such geo-referenced information on support practices is scarce or not available in countries of the Global South. Remote sensing-aided mapping of soil conservation structures and associated P factor quantification have till date not yielded fruitful results either (Mekuriaw, 2014, as cited in Haregeweyn et al., 2017), making the P factor the hardest parameter to estimate in large-scale USLE applications, and often compelling researchers to ignore it altogether (Jain and Das, 2010; Mondal et al., 2015; Borrelli et al., 2017; Bhattacharya et al., 2020a,b). In India, however, two main support practices are observed in croplands– contouring and field bunding is widespread in the plains and plateau fringes, while terraces (both graded and levelled) are observed in the Himalayas and other hilly regions (Das, 1977; Dhruva Narayana and Sastry, 1985). Wischmeier and Smith (1978) have provided a table to estimate the P factor values for contoured croplands based on slope classes (Table 11), and Renard et al. (1997) proposed a similar scheme of P factor estimation for terraced fields (Table 12) that can be combined with the P factor derived for contouring and stripcropping tracts wherever necessary. In the absence of requisite information to objectively estimate the P factor for non-croplands, we, following the suggestion of Karpilo and Toy (2003), recommend considering it constant at 1.0, which is rather common in contemporary USLE-based soil erosion modelling (Koirala et al., 2018; Almaw Fenta et al., 2019).

Table 11: P factor values for contouring and contour bunding (Wischmeier and Smith, 1978)

Slope (%)	1–2	3–5	6–8	9–12	13–16	17–20	21–25	>25
P factor	0.6	0.5	0.5	0.6	0.7	0.8	0.9	1.0

Table 12: P factor values for terracing (Renard et al., 1997)

Terrace width (m)	<33.53	33.53–42.67	42.67–54.86	54.86–68.58	68.58–91.44	>91.44
P factor	0.5	0.6	0.7	0.8	0.9	1.0

5.6 Evaluation of modelled erosion rates

Like the outputs from other environmental models, modelled soil erosion rates/amounts must be evaluated against empirical evidence (Batista et al., 2019). However, the ‘validation’ of soil erosion models is rather difficult, if not impossible, since observed soil losses are themselves frequently as uncertain as the modelled outputs (Alewell et al., 2019; Batista et al., 2019, 2021). A recent global review of soil erosion modelling studies (Borrelli et al., 2021) revealed that the overwhelming majority of model validation attempts were based on comparing the sediment yield observed at a catchment's outlet to the predicted soil erosion from it, even though it can be justifiably questioned whether the measured and modelled data represent the same fluxes or not (Alewell et al., 2019; Borrelli et al., 2021). This especially holds true for USLE-type models that are only capable of predicting on-site rill and interrill erosion at the plot/field-scale and not off-site catchment sediment yield (Trimble and Crosson, 2000). The results of a recent USLE-based modelling study in the East Africa region (Almaw Fenta et al., 2019), when compared with observed catchment-level sediment yield data of 100 catchments, elicited a coefficient of determination of only 0.39. However, the USLE-modelled soil loss rates compared much better against the observed soil losses from a small agricultural watershed of 973 ha in India, with a coefficient of determination of 0.71 (Singh and Panda, 2017) and when applied and compared at the field-scale, the coefficient of determination was considerably higher at 0.88–0.91 (Ali and Sharda, 2005).

Sediment yield rates are always lower than soil erosion rates, as most of the eroded soil is deposited within the catchment during its transfer, along gentler declivities or within areas of poor hydrological and sediment connectivity (Boardman et al., 2018; Baartman et al., 2020). Furthermore, the sediment yield measured at the catchment outlet is a combined output of all erosion/transport processes acting therein (Morgan, 2005), and not just the rill and interrill erosion that the USLE simulates. Therefore, using catchment sediment yield records to evaluate on-site USLE-modelled soil losses is not always appropriate. Measured soil loss or sediment yield records are scant anyway in Global South nations (Garcia-Ruiz et al., 2015; Borrelli et al., 2021; Batista et al., 2021), which is why most USLE-based modelling studies are unsurprisingly deterministic in nature, with little attempt made to evaluate their results through comparison with other soil erosion modelling studies. This is certainly valid in the Indian context, as three quarters of the studies reviewed here did not attempt any kind of evaluation and only 12 studies compared the USLE derived output to that obtained from other modelling approaches. Of the remaining 13 papers, nine attempted a quantitative evaluation using observed catchment/basin sediment yield, two studies validated their results against measured hillslope or plot-scale soil losses, just one paper assessed the uncertainty of the modelled soil erosion rates while another compared the soil erosion map generated from the USLE to that area's microwatershed erosion and runoff potential map as prepared by the Soil and Land Use Survey of India (SLUSI).

Interestingly, SLUSI has produced a potential erosion priority map at a scale of 1:50000 by computing the Sediment Yield Index (SYI) and Runoff Potential Index (RPI) through a multicriteria-based decision making and weightage assignment approach for 321324 micro-watersheds across the country, covering 2.61 million square kilometres, which is ca. 80% of India's entire territory. This exercise, conceived principally for the purpose of watershed management in the catchment areas of major river valley projects and other flood-prone rivers, was initiated in the 1970s and completed in 2012. Each micro-watershed was classed under one of the priority categories, namely very high, high, medium, low and very low, according to the calculated SYI and RPI values. This approach was purely subjective and was only devised to obtain a relative ranking of the respective runoff volumes and erosion vulnerability of these sub- and micro-watersheds. As such, the SYI and RPI values do not correspond in any way to actual sediment yield and runoff volumes (SLUSI, 2021a). Moreover, the most erosion-prone regions of the country were surveyed before 2000 (SLUSI, 2021b), making this database somewhat dated as well. Most importantly, as there is no objective means to classify a USLE soil loss map in a manner congruent to the SLUSI micro-watershed prioritisation strategy, its use is not recommended to assess the accuracy of soil erosion rates modelled through the USLE.

With a view to improving the verifiability of future USLE applications in India, we hereby propose a novel procedure for evaluating the accuracy of modelled soil erosion maps in India using a remote sensing-based product and also include some general comments on the model uncertainty analysis.

5.6.1 Evaluation of the derived USLE soil loss map

The NRSC has produced comprehensive land degradation maps of India corresponding to the years 2005-06 and 2015-16, at a scale of 1:50000, through visual inspection and image classification of Resourcesat-2 LISS-III 23.5 m imagery, subsequently verified by ground truthing. These datasets, available from the Bhuvan Geo-portal (https://bhuvan.nrsc.gov.in/), highlight eight land degradation types, viz. water erosion, wind erosion, water-logging, salinisation/alkalisation, acidification, glacial weathering, anthropogenic and other processes, that are further classified into 36 categories (NRSC, 2019b). However, for the purpose of assessing the USLE model output, only three severity classes of the water erosion type are needed, i.e. Sheet erosion – Slight, Sheet erosion – Moderate and Sheet erosion – Severe, which correspond, on average, to soil erosion rates of 10-20, 20-40 and >40 t ha^{-1} yr^{-1}, respectively. Logically, areas that are not characterised by soil loss rates of greater than 10 t ha^{-1} yr^{-1} can be considered to have erosion rates <10 t ha^{-1} yr^{-1}. However, being a remote sensing-based product, the sheet erosion severity classes were mapped by visual interpretation of the surface manifestations of soil erosion. Though these interpretations were field verified, the exact severity of the problem is often difficult to estimate with naked eyes (NRSC, 2019b). Therefore, the stated corresponding soil erosion rates are only indicative, rather than being strictly prescriptive. They nevertheless provide a suitable means for assessing both the catchment and regional scale soil erosion risk in a spatially-explicit manner.

Just like the Bhuvan LULC datasets, these land degradation maps can be loaded as a WMS layer in a GIS and subsequently saved as GeoTIFF files. Performing an unsupervised classification renders them ready for further analysis and manipulation. A USLE-produced soil erosion map is best evaluated against the NRSC devised sheet and rill erosion map by creating an accuracy map. To generate this, the USLE output must first be reclassified akin to the classification of the NRSC map, i.e. into soil erosion classes of <10, 10-20, 20-40 and >40 t ha^{-1} yr^{-1}. If these four classes are numbered respectively as 1, 2, 3 and 4 in both sets of reclassified maps and subsequently multiplied, the areas (pixels) of correct prediction will bear the numbers 1, 4, 9 and 16, i.e. squares of 1 through 4. It would mean that for these areas, the USLE-based estimate of the soil erosion severity was the same as that denoted in the NRSC dataset. Of course, this method elicits a comparison of the accuracy of value ranges rather than specific/individual cell-wise discrete values. However, in the current data sparse scenario, we feel that this is perhaps the most objective and simple way of evaluating USLE derived outputs in India.

5.6.2 Uncertainty analysis of USLE soil loss map

Soil loss rates predicted by the USLE are known to be highly uncertain (Schurz et al., 2019; Batista et al., 2021), in no small part due to input data unavailability or quality and associated problems regarding model parameterisation, rather than any inherent failure of the model itself (Fischer et al., 2018). This is especially true for studies conducted in developing countries, where adequate datasets are not usually available for robust model parameterisation. Therefore, uncertainty analysis of the modelled output becomes vital (Swarnkar et al., 2018; Batista et al., 2021). The most common uncertainty analysis methods are Markov Chain Monte Carlo (MCMC) (Gasparini, 1995) and Generalised Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992). Biesemans et al. (2000) applied the MCMC error propagation technique to RUSLE, while Batista et al. (2021) and Rosas and Gutierrez (2020) showed how to implement the GLUE methodology in a USLE-based soil erosion modelling study at the catchment and regional scales, respectively. Swarnkar et al. (2018) proposed a rather simple first-order error analysis method for modelling soil erosion using USLE in large river basins in India, by separately accounting for uncertainties in the different factors. As the above cited studies present appropriate uncertainty analysis methodologies for USLE-type soil loss modelling with adequate clarity and details, we refer to them, instead of proposing or demonstrating a similar method ourselves. Such uncertainty analysis combined with model evaluation according to the procedure explained in section 5.6.1 and demonstrated below would surely further the verifiability of modelled outputs and improve manifold the overall quality of future USLE applications in India.

5.7 Modelling a correctly parameterized USLE - a test application

We demonstrate the applicability and accuracy of the afore-suggested USLE factor estimation methods to model soil erosion in the Upper Brahmani river basin in eastern India (Fig. 7), and thereafter evaluate the extracted soil erosion map using the NRSC land degradation dataset of 2015-16. This basin is formed by the tributaries of the River Brahmani, viz. the South Koel and the Sankh. The latter originates from the Netarhat region of the Chhotanagpur plateau while the source of the former is at Lohardaga, on the other side of the water divide from where the River Damodar arises (Behera et al., 2020). The basin area is 19330 km^2., of which 15280 km^2 is in the state of Jharkhand, 2625 km^2 lies in Odisha and the remaining 1425 km^2 is in Chhattisgarh. The basin elevation ranges between 155 m and 1116 m a.m.s.l. Deciduous forest is the largest land cover class of the basin, occupying 34% of its area, followed by croplands and fallow that cover 31% and 18% of the basin area respectively. The climate is of *Aw* (Tropical hot and dry) type, with annual temperatures and rainfall ranging between 4–47° C and 1022–1618 mm, respectively. The Chhotanagpur plateau is naturally erosion-prone due to the undulating physiography of the region and rapid deforestation in some parts causes especially severe soil erosion (Roy Mukherjee, 1995), among which the Upper Brahmani basin area stands out due to the rather large differences between its soil loss tolerance and soil erosion rates (Sharda et al., 2013).

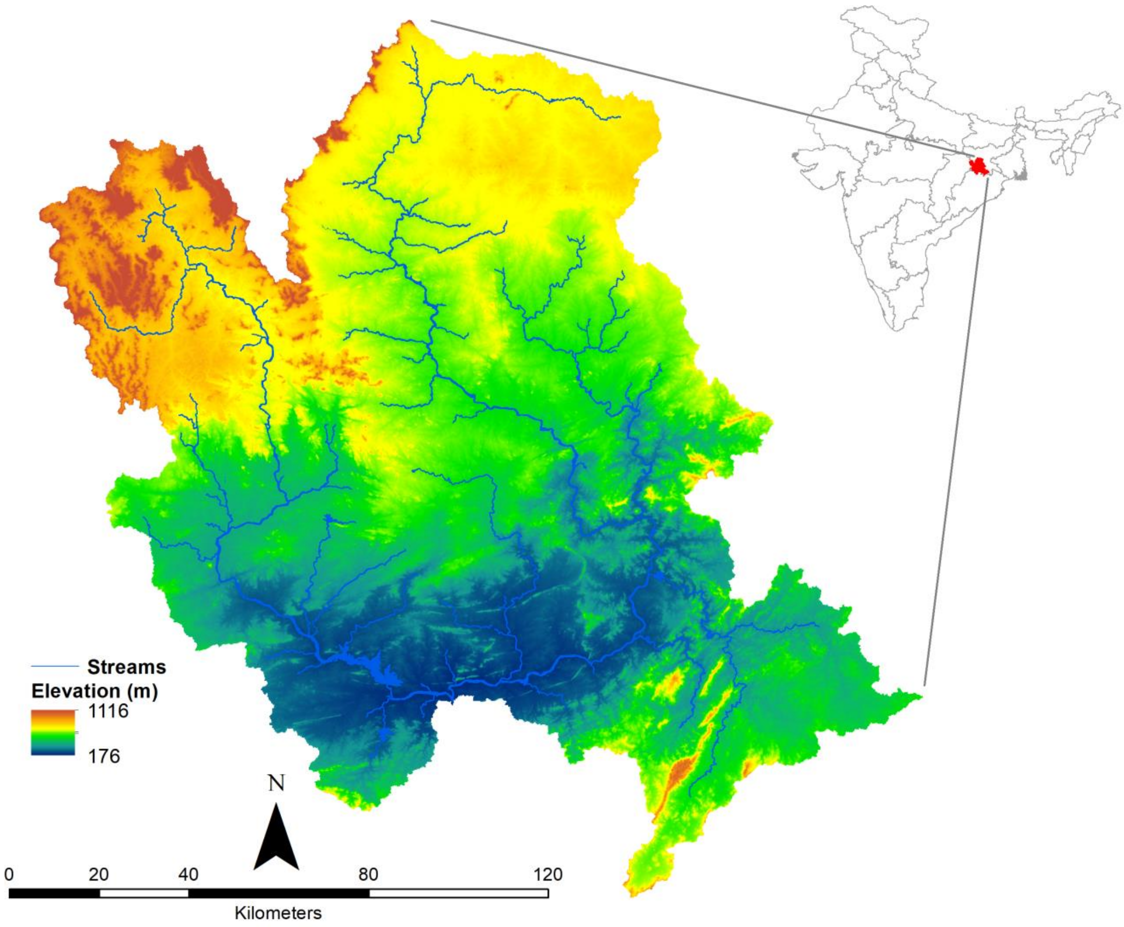

Fig. 7: Location map of the Upper Brahmani basin

All the USLE factor maps (Fig. 8) were prepared according to the procedures elucidated in sections 5.1 through 5.5. For making the R factor map, a mean annual precipitation surface (1 km horizontal resolution) was prepared through ordinary kriging with spherical variogram using mean annual precipitation data (25–40 years records) of 111 weather stations located in and around the Upper Brahmani basin. We obtained topsoil (0–30 cm) texture and organic carbon content layers from ISRIC SoilGrids (https://soilgrids.org/) to estimate a spatially continuous depth-averaged soil erodibility (as per Auerswald et al., 2014) map for the basin at a resolution of 250 m. In order to identify the appropriate channel initiation threshold in this area, high-resolution imagery from the OpenStreetMap platform (https://www.openstreetmap.org/) and a flow accumulation surface derived from the 30 m resolution SRTM DEM was used and the threshold was found to be ca. 25 pixels or 2.25 ha on average. Therefore, all pixels with a flow accumulation value greater than 25 were left out and we finally only considered slope lengths shorter than or equal to 122 m, as is the convention. The C and P factors (at 30 m resolution) were derived from the LULC map of NRSC (2019a) corresponding to 2015-16 through the respective procedures outlined before.

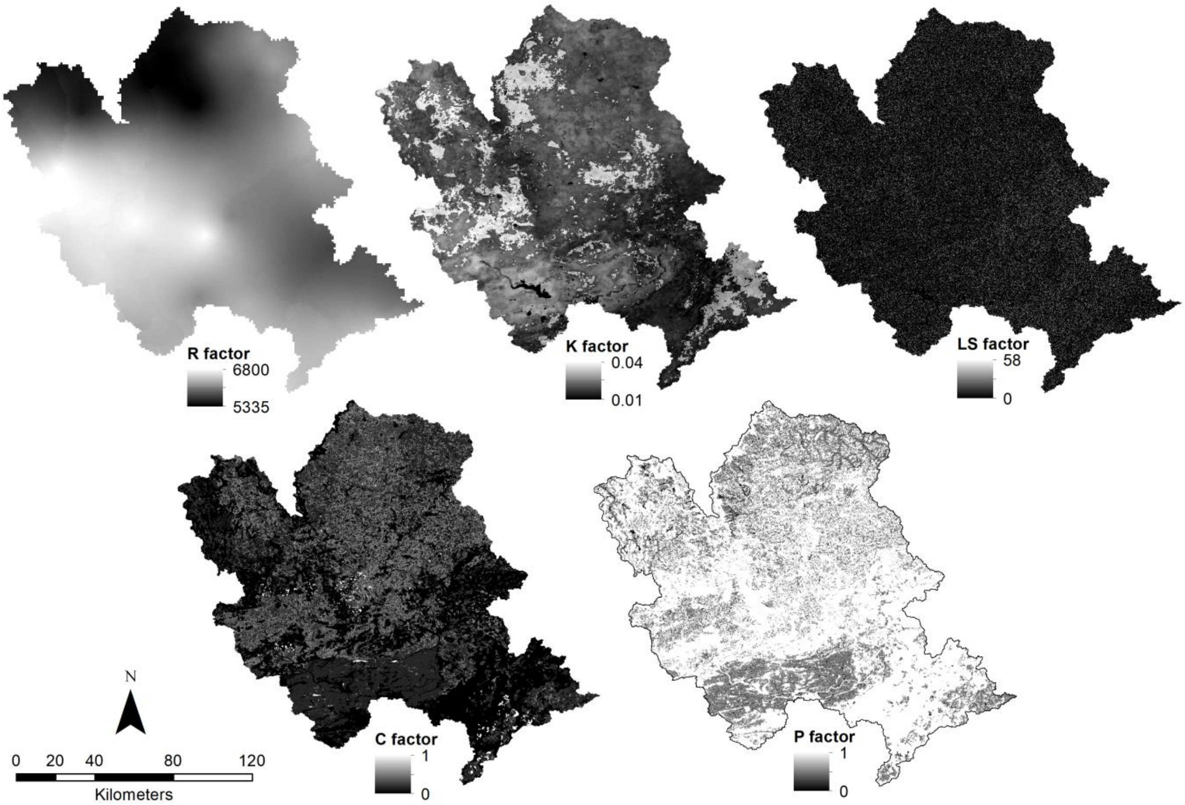

Fig. 8: USLE factor maps (with R and K factors in SI units) for the Upper Brahmani basin

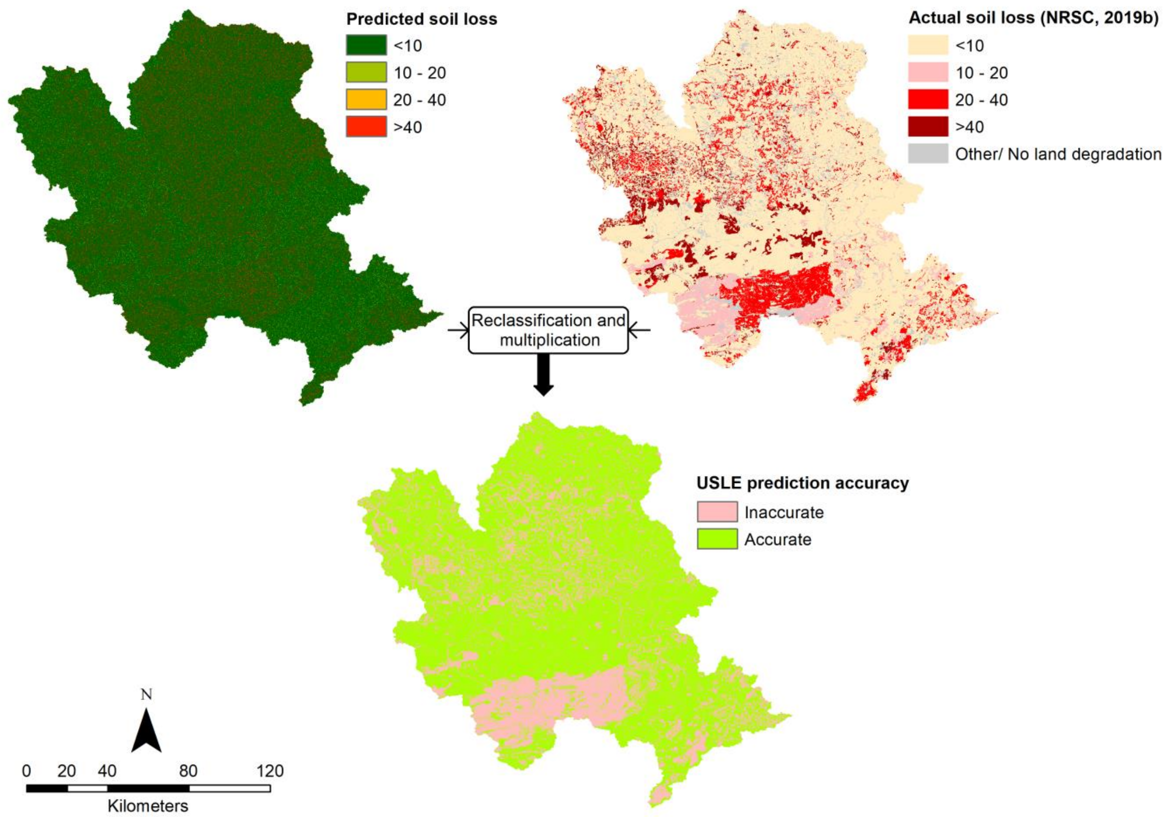

Fig. 9: Spatial distribution of predicted and actual soil loss rates in t ha^{-1} yr^{-1} and a spatially-explicit evaluation of USLE prediction accuracy in the Upper Brahmani basin.

Compared according to the procedure outlined in section 5.6.1, the modelled soil loss rates predicted by the USLE corresponded quite well to the actual soil loss rates in this region estimated by NRSC (2019b), with an overall accuracy of 79.6% (Fig. 9). This relative accuracy analysis reveals that only near the catchment mouth a substantial zone of mismatch exists between these two outputs.

5.8 Using this review's findings beyond India

Across the Global South (and indeed in many other places too), USLE applications may be more vulnerable to inappropriate/ incorrect parameterisation, due to want of requisite data in general and the lack of local/regional research on individual USLE factors. Through our review, we have sought to outline some best practices, such as being mindful of the regional specificity and applicability of the R factor computation methods prevalent in the literature, the viability of the USLE K factor nomograph equation set developed by Auerswald et al. (2014) when used in combination with ISRIC SoilGrids data, general considerations regarding the LS factor's estimation from open-source elevation datasets and nuances of the

C and P factors' estimation when using readily available land cover/use maps. These principles/considerations are applicable worldwide.

Furthermore, with India being located in the monsoonal tropics where precipitation and hence soil erosion has a characteristic strong seasonality, our suggested best methods and parameters are especially applicable in the rest of Monsoon Asia or South Asia, South-East Asia and other regions of the world that have similar climatic regimes and intensive land use practices. The R factor methods of Babu et al. (2004) as discussed in Section 5.1 can be feasibly used in areas receiving monsoonal rain of up to 3500 mm on an annual basis and thus by default is able to estimate the rainfall erosivity factor from gauged precipitation data anywhere in monsoon Asia, if the country in question does not have a local R factor estimation method, viz. Nepal, Bhutan, Bangladesh, Sri Lanka and Myanmar.

Although the NRSC land cover datasets are only available for Indian territories, the C and P factor computation schemes as outlined in Section 5.4 and 5.5 will be relevant even when applied outside of India using similar databases. The C factor values for the various crop types and non-arable land cover classes collated in Section 5.4 represent, in most cases, the soil loss sensitivity of the respective land cover types in subtropical and monsoonal climates. The Copernicus Global Land Service (https://land.copernicus.eu/global/products/lc) has made available data on a number of bio-geophysical properties of the land surface, including land cover/use maps that can be utilised in absence of national land cover classification and as hinted by Borrelli et al. (2017, 2020), requisite data on crop acreage can be conveniently procured from the FAOSTAT database (http://www.fao.org/faostat/en/#data) of the Food and Agriculture Organization (FAO), if the same is not available from the concerned national data repositories.

Just like the NRSC land cover datasets, the land degradation maps prepared by NRSC only pertain to Indian territories. However, besides model uncertainty analysis, spatial assessment of the produced soil erosion maps (as demonstrated in Section 5.6.1) can be undertaken through comparison with global land degradation datasets such as the Global Assessment of Human-induced Soil Degradation (GLASOD) (Oldeman et al., 1991) and Global Assessment of Land Degradation and Improvement (GLADA) (Bai et al., 2008). The GLASOD database, which has already been used to evaluate global soil erosion assessments (Borrelli et al., 2017, 2020), comprises of the type, extent, degree, rate and causes of degradation within physiographic units at a scale of 1:10 million, based on expert judgement. It was the result of an international data compilation initiative wherein more than 300 soil scientists across the world contributed data collected using uniform guidelines and international correlations based on extensive field observations (Oldeman et al., 1991). However, the qualitative GLASOD maps lack recency, having been compiled during the 1980s. The GLADA followed up on the GLASOD through a more detailed and accurate assessment of the land degradation status and trends by means of integration of time series analyses of the NDVI parameter for the years 1981–2003 with climatic, land cover and terrain data (Bai et al., 2008). Although this dataset highlights land degradation and not directly soil erosion, it has also been successfully used to examine USLE-based soil erosion estimates (Borrelli et al., 2017, 2020).

6. Concluding remarks

This review has sought to highlight the fallacies apparent in past studies that have used the USLE to estimate soil erosion in India at varied spatial scales. We have succinctly highlighted the nature of each of the parameters that constitute the USLE and the RUSLE models together with the range of methods and equations that have been proposed to compute them. At the same time, through a detailed review, we have highlighted the potential shortcomings of a substantial number of studies that have either misinterpreted these parameters, computed them based on misassumptions or misrepresented the units of the values derived. This has caused over- and under estimation of modelled soil erosion values in a large number of cases. The stark disparity between the derived values and those to be expected from correctly parameterised, computed and represented studies is not only statistically significant but also quite troubling, given the apparent dearth of accurate information in many of the studies and their possible duplication in ensuing analyses, thereby likely compounding mistakes even further. We also find the failure of many studies to properly document their methods in detail for each parameter and forgo the subsequent model accuracy and uncertainty analysis to be a cause for further concern. This has urged us to try and identify the best possible methods and ways to devise and conduct a test-case of the USLE in India, based on available open-source datasets and also present its accuracy estimates. We hope that the detailed discussions of the different factors presented here and the highlighting of possible missteps in their implementation can better inform future USLE based soil loss modelling studies in India, through more accurate, considered and context and area-specific model parameterisation.

Our review also highlights a concentration of USLE studies in only some parts of India with scant attention accorded to regions where the model's application may be most desirable to gauge the ongoing soil loss. Correct applications of this model in these regions can further soil loss management plans for the most affected portions of the country and increase their spatial ambit. Furthermore, we have outlined the general principles/considerations that govern any USLE-based soil erosion modelling exercise and these are applicable not only in the Indian context but in any such study worldwide, particularly in regions that have similar climatic and cropping regimes to India, wherein the best methods and equations we have highlighted can be feasibly employed for quite accurate estimations of the soil loss, either using local datasets or suggested global repositories.

Another big step towards improving the USLE's applicability in India would be the generation and regular updation of higher resolution hydrological, climate, soil and topographic datasets. The product of the official soil erosion modelling endeavour of India was an isopleth map at a rather coarse resolution of 10 km (Maji et al., 2008; Sharda et al., 2013), and more research is certainly warranted, using state-of-the-art data, to develop refined, high resolution datasets at a pan-Indian scale to model soil erosion in general and facilitate USLE applications in particular. For instance, Babu et al. (2004) deduced the rainfall erosivity-precipitation relationships by analysing the relevant data up to 1995. Their devised equations thus lack recency, especially given the recent climate change effects on the precipitation regime of India (Kulkarni et al., 2020). Moreover, even though rainfall erosivity estimation methods based on the Modified Fournier Index (Arnoldus, 1980) are used all over the world (Benavidez et al., 2018), no such method yet exists to specifically predict the R factor in India. A re-analysis of precipitation-erosivity relationships in the country is thus pertinent to assess the performance of existing techniques and to develop revised R factor estimation methods, as and where necessary. Similarly, there is a pertinent need for a nationwide high-resolution digital soil erodibility map together with comprehensive country-wide mapping and decadal change analysis of the cover and management factors, in order to identify potential erosion hotspots so that the commensurate soil erosion control works may be undertaken more fruitfully.

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