Chapter 7
Soil Loss Estimation Using Models and Field Database in Lateritic Badlands, Eastern India: Evaluation and Validation

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Abstract The key purpose of this chapter is to determine the suitability and applicability of index-based erosion models for the precise estimation and prediction of annual soil erosion rates under the monsoon-dominated geo-climatic and land use systems. The study unit is represented as the lateritic badlands of Dwarka–Brahmani River Basin (Eastern India). The present study finds a variable range of annual erosion rates (8.12–24.01 kg m^{-2} $year^{-1}$ as measured data) at hillslope scale of watershed (i.e. basins of permanent gullies) using popular models of Revised Universal Soil Loss Equation (RUSLE) and Revised Morgan-Morgan-Finney (RMMF), sedimentation pits and field measured data (2016–2017). The important part of this experimental design and quantitative analysis, used to assess the effectiveness of models, is to compare the forecast given by model to field measured data. The regression analysis of experimental results show that there is a positive correlation and increment between measured and predicted erosion data in RUSLE modelling ($Y_c = 5.90 + 0.659\ X$, $R^2 = 0.521$), but an inverse relation and negative increment are observed in RMMF modelling ($Y_c = 16.27 + 0.162\ X$, $R^2 = 0.212$). The indices of model evaluation and testing statistics have confirmed the reliable performance (best fit to observed erosion rate) of RUSLE over RMMF. The potential erosion map of area depicts annual erosion rate beyond the tolerance limit (1.0 kg m^{-2} $year^{-1}$). It is estimated that the mean soil depth of 0.95 cm $year^{-1}$ is permanently lost from the surface of lateritic catchments, and the water erosion will require typically 176 years to erode the mean soil thickness of 1500 mm.

Keywords Soil erosion · Land degradation · Gully erosion · Laterite · Soil loss tolerance · RUSLE · RMMF model

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7.1 Introduction

Soil erosion is regarded as one of pervasive geomorphic hazards in Anthropocene and taking immediate steps and management actions to preserve our soil resources should need no explanation (Bell, 2002; Lal, 2012; Poesen, 2018). Soil erosion is now referred to as the most important factor of land degradation and globally; about 30% of land areas are estimated to be degraded in this condition of environmental change, affecting almost 3.2 billion people (mainly Brazil, China, Ethiopia, Indian and Spain) (Wen & Deng, 2020). Erosion visibly degrades landscapes through exposure of sub-soil, presence of rills and gullies or the occurrence of dust storms. Land degradation can be defined as a negative trend in land potentiality, caused by direct or indirect human-induced processes including anthropogenic climate change, slope modification, deforestation and land use changes, expressed as long-term reduction or loss of at least one of the follows: biological productivity, ecological integrity or value humans and soil productivity (Nkonya et al., 2016). In the Anthropocene, soil losses by human activities (i.e. anthropogenic soil erosion) have also become very significant: e.g. tillage erosion, soil erosion by land leveling, soil quarrying, crop harvesting, explosion cratering and trench digging (Bocco, 1991; Poesen, 2019). During the past 60 years, many studies and researches have documented variable magnitude of soil erosion problems in different parts of the world (especially in India) (Table 7.1 and Fig. 7.1), expressed as billions of tons of eroded soil or billions dollars of erosion and sedimentation damage each year (Narayana & Babu, 1983; Bocco (1991); Kothyari, 1996; Lal, 1990; Singh et al., 1992; Wasson, 2003; Vente & Poesen, 2005; Pimentel, 2006; Reddy & Galab, 2006; Thakkar & Bhattacharyya, 2006; Kumar & Pani, 2013; Pimentel & Burgess, 2013; Sharda et al., 2013; Sharda & Dogra, 2013; Aulakh & Sidhu, (2015); Borrelli et al., 2017; Froechlich, 2018; Sharma, 2018; Poesen, 2018; Pennock, 2019).

Soil erosion is defined as the net long-term balance of all processes that detach soil particles and move it from its original location through sheet flow, rill and gully channels (Eekhout & Vente, (2019); Pennock, 2019). In the Indo-Gangetic Plain, the world's larger alluvial plain and other agricultural regions of India, soil erosion by water is the most serious cause of land degradation (Marzolff & Pani, 2019). It affects 64% of the estimated area of 147 m ha of degraded wasteland in the country (Marzolff & Pani, 2019). It estimated an annual average potential soil erosion amounting 35 Pg year^{-1} for 2001 and in 2012, an overall increase of 2.5% in soil erosion (Borrelli et al., 2017). RUSLE-based modelling approach predicts global potential soil erosion rates of 43 Pg year^{-1}, and due to climate change and land use transformation, average soil erosion can be increased from 30 to 66% in between 2015 and 2070 (Borrelli et al., 2020). About 5–7 million ha (12.4–17.3 million acre) of arable land in the world is degraded annually through various erosion processes, and out of 2 billion ha (4.9 billion acre) of degraded area in world, water erosion alone, being a global phenomenon, contributes about 55% (Fig. 7.1) (Sharda et al., 2010). Among the soil groups of India, red–lateritic soils (mostly alfisol, inceptisols and utlisols) and black soils (vertisols and vertic subgroups) acutely suffer due to

Table 7.1 Key information and findings on soil erosion issues in India

Sl. no.	Important facts and research outcomes	Source
1	Annual soil erosion is taking place at the rate of 16.35 t ha^{-1} $year^{-1}$	Narayana and Babu (1983)
2	Indo-Gangetic Plains of Punjab, Haryana, Uttar Pradesh, Bihar and West Bengal are affected by erosion rate of 5 to 10 t ha^{-1} $year^{-1}$	Singh et al. (1992)
3	About 20% of India's existing reservoirs will have lost 50% of their previous storage capacity due to soil loss and siltation	Kothyari (1996)
4	3.975 million ha of wastelands are severely affected by gullies and ravines	Yadav and Bhushan (2002)
5	Due to siltation, India is losing about 1.3 billion m^3 of storage capacity each year and to create this storage capacity India will require Rs. 1448 crores	Thakkar and Bhattacharyya (2006)
6	Paddy is the most affected among all crops in terms of both productions 4.3 million tonne and monetary loss of Rs. 24.4 billion	Sharda et al. (2010)
7	The Lower Gangetic Plain and eastern part of Chota Nagpur Plateau has soil loss tolerance level of 2.5–12.5 t ha^{-1} $year^{-1}$	Bhattacharyya et al. (2007); Mondal and Sharda (2011)
8	India suffers an annual loss of 13.3 million tonne in production of cereals, oilseeds and pulses due to water erosion	Sharda et al. (2013)
9	About 69.5% area of India has soil loss tolerance limit of <10 t ha^{-1} $year^{-1}$	Sharda and Dogra (2013)
10	About 5.4 million tone of fertilizer worth US $ 245 million is washed away by water erosion	Gulati and Rai (2014)
11	Erosion escalates the siltation rate of reservoirs in India–Maithon (1.076 mm $year^{-1}$), Panchet (0.631 mm $year^{-1}$), Tilaiya (2.792 mm $year^{-1}$), Tenughat (0.716 mm $year^{-1}$), Durgapur barrage (0.042v), Kangsabati (0.752 mm $year^{-1}$) and Massanjore (0.557 mm $year^{-1}$)	Central Water Commission (2015)
12	The soil pool loses 110 Mt Carbon into the atmosphere due to soil erosion. It is projected that 1% increase in rainfall intensity may increase the rainfall Erosivity by 2–6%. Annual loss due to soil degradation ranges from Rs. 89–232 billion	Bawa (2017)
13	1 mm loss of soil from one hectare land, an additional 1642 MJ of energy is expended, which is equivalent to about 91 kg of petrol	Sharda et al. (2019)
14	It is estimated from satellite images that 9593.06 km^2 land of India (17.09 km^2 land of West Bengal) is affected by gullies and ravines	National Remote Sensing Agency, NRSC (2019)
15	In a river basin of semi-arid region, soil erosion risk was assessed using RUSLE and frequency ratio probability algorithm to prioritize erosion susceptible areas	Gayen et al. (2020)

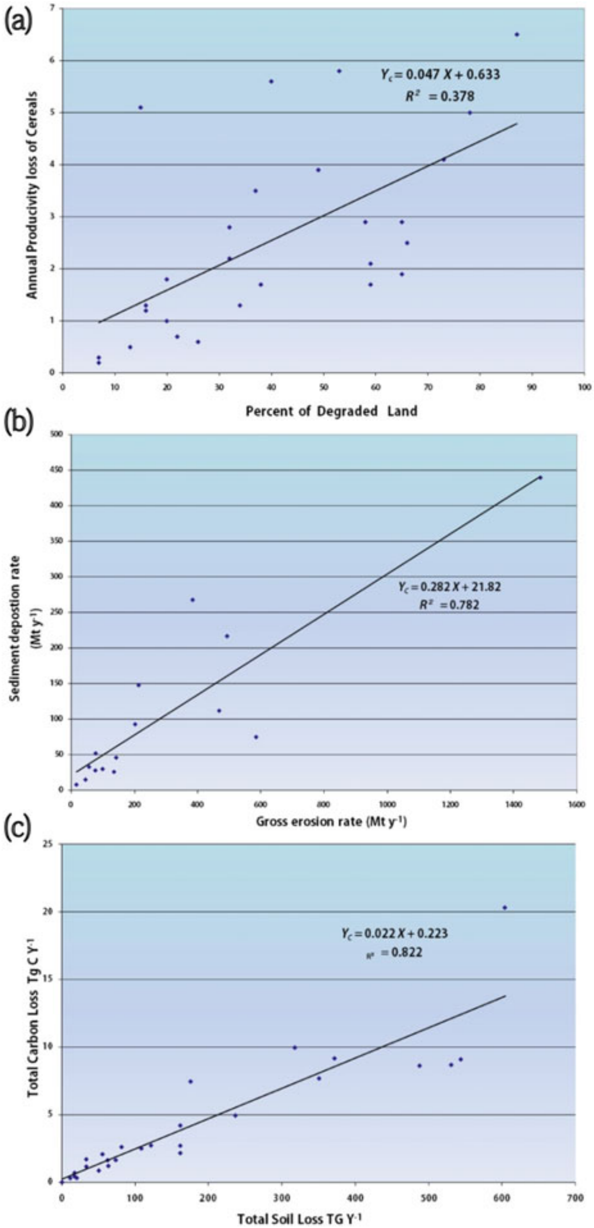


Fig. 7.1 Important research findings of soil erosion hazard in India—(**a**) with increasing percentage of state-wise degraded land the production loss of cereals is also rising, (**b**) there are a positive correlation and increasing trend in between gross erosion rates of river basins and sediment deposition rates of reservoirs and (**c**) total carbon loss from land is escalating with increasing soil loss in India

water erosion (Table 7.2). It is estimated that 120.72 million ha area is affected by various forms of land degradation and desertification in India with water erosion being chief contributor (68.4%) (Sharda et al., 2013). About 69.5% area of India has soil loss tolerance limit of <10 t ha^{-1} year^{-1}, while about 13.3% area has a soil loss tolerance limit of only up to 2.5 t ha^{-1} year^{-1} (Sharda & Dogra, 2013). In India

Table 7.2 Expected and average values of loss of soil productivity due to water erosion in different soils of India (Sharda et al. (2010)

Erosion class	Soil loss (t ha^{-1} $year^{-1}$)	Loss in productivity (%)		
		Alluvial soils	Black soils	Red soils
Very slight	<5	0.0	2.5	5.0
Slight	5–10	2.5	7.5	17.5
Moderate	10–20	7.5	17.5	37.5
Strong	20–40	17.5	37.5	60.0
Severe	>40	37.5	60.0	–

major rainfed crops suffer an annual production loss of 13.4 Mt due to water erosion which amounts to a loss of Rs. 305.32 billion in monetary terms (Ghosh et al., 2020).

It is now understood that soil erosion is a pertinent issue where the adage 'think globally, act locally' is clearly applicable (Toy et al., 2013). The essential purpose of quantitative assessment is that erosion control targeted toward the areas with the highest rates can markedly reduce erosion averages. Before taking any erosion protection measures, the estimation of annual erosion rate at plot to basin scale is the fundamental step towards achieving soil conservation and sustainable development (Toy et al., 2013). Models can serve a needful purpose of soil conservation which acts to make broad-scale erosion surveys in order to realize the existing problem over an erosion-prone lateritic region of tropical monsoon climate and to track changes in erosion over time (Nearing, 2013). Modelling and prediction of soil erosion by water has long legacy and preliminary popular studies published in various international journals probably seven decades ago using North American data sets (Bennett, 1939). The largest number of publications with the application of Revised Universal Soil Loss Equation (RUSLE) model has been found in the USA (274 papers), China (218 papers), Brazil (88 papers), India (67 papers), Spain (66) papers), etc. Up to 2017, 1556 research papers have been published at various spatial scales (1977–2017) (Alewell et al., 2019; Yanshuang et al., 2020). Many mathematical models categorized as empirical or index-based, conceptual, physically based or process-oriented are variable to estimate soil erosion at different spatial and temporal scales (Wischmeier & Smith, 1978; Renard et al., 1997; Morgan et al., 1998; Flanagan et al., 2001; Morgan, 2001; Merriti et al., 2003; Avwunudiogba & Hudson, 2014; James et al., 2017; Morgan & Duzant, 2008; Alewell et al., 2019; Pennock, 2019; Gayen et al., 2020; Yanshuang et al., 2020).

The data availability on land degradation, soil erosion rates and permissible soil loss limits is either qualitative or insufficient for proficient planning of conservation and management of erosion intensity at watershed or regional scale (Sharda et al., 2013). The criterion for judging whether the soil has potential risk of erosion or not is essentially required for adopting appropriate erosion control measures on grazing land, arable land, barren land and other land use systems (Sharda et al., 2013). Realistic assessment of erosion risk or soil loss rate thus constitutes the first step for understanding the ground reality of erosion and raising awareness among governmental and other stakeholders in a given region to adopt appropriate strategies for sustainable and efficient use of natural resources for the current and future generations (Sharda et al., 2013). Erosion protection measures should start from microscale to get long-term soil productivity and long-term sustainable agriculture in the developing counties, like India, where erosion protection technologies are limited by economic and other cultural conditions. In addition, it is necessary to state that the laterite terrain of West Bengal (known as *Rarh* Plain, i.e. the land of red soil) is severely dissected by the dense network of rills and gullies (Ghosh & Guchhait, 2017), developing badland topography, and there are very few databases of accurate annual erosion rates and empirical model applications. The lateritic *Rarh* region and plateau fringe (districts of Purulia, Bankura, Paschim Barddhaman and Paschim Medinipur) show lower T value ranging from 2.5 to 5.0 Mg ha^{-1} year^{-1} (Mondal & Sharda, 2011; Lenka et al., 2014). In West Bengal as a whole, about 88% of the area is identified as T value zone of 12.5 Mg ha^{-1} year^{-1} (Mondal & Sharda, 2011; Lenka et al., 2014). In this regard, this study can give few insights on the aspect of soil erosion modelling using minimal data inputs and measured plots at basin scale to estimate annual erosion rate in the lateritic badlands. Two major objectives of the study are set forth as follows:

(1) To estimate annual soil erosion rate using models and field experimental database
(2) To evaluate suitability and effectiveness of model in the study area

7.2 Geographical Setting of Study Area

The geomorphic unit of study is recognized as the badlands (interfluves) in between Brahmani (north) and Dwarka (south) rivers (encompassed by 24° 20′ N to 23° 40′ N, and 87° 26′ E to 88° 21′ E) (Fig. 7.2). This geomorphic region is recognized as plateau proper and plateau fringe of Chota Nagpur, prevailing the patches of laterite exposures and basaltic hills, and it is categorized as the northern part of the *Rarh* Plain (Biswas, 1987). Geologically, the interfluve is associated with the contiguous unit between Rajmahal Basalt Traps (RBT) (Early Cretaceous origin) and the Bengal Basin which exhibits shallow Quaternary alluvium deposits. The palaeogenesis of the deep weathering profiles under intense tropical wet–dry palaeoclimate on the basaltic surface formed hard ferruginous crust, i.e. *Ferricrete* (Palaeogene–Early Pleistocene) (Ghosh et al., 2020).

The sample study area of laterite interfluve (about 176 km^2, encompassed by 24°08′N to 24°14′ N and 87°38′ E to 87°44′ E) covers Shikaripara block (Dumka, Jharkhand) and Rampurhat I and Nalhati I blocks (Birbhum, West Bengal) (Fig. 7.3). Field study reveals successive occurrences of fresh quartz-normative tholeiite Rajmahal basalt, weathered coarse saprolite, kaolinite pallid zone, mottle zone and pisolitic ferricrete in the litho-sections (Ghosh & Guchhait, 2015). Each laterite section reflects both primary in situ-type palaeogenesis of high-level plateau laterites (Chorley et al., 1984) and secondary ex situ evolution of piedmont slope laterites which are prone of to water erosion, forming patches of badlands in the *Rarh* Plain.

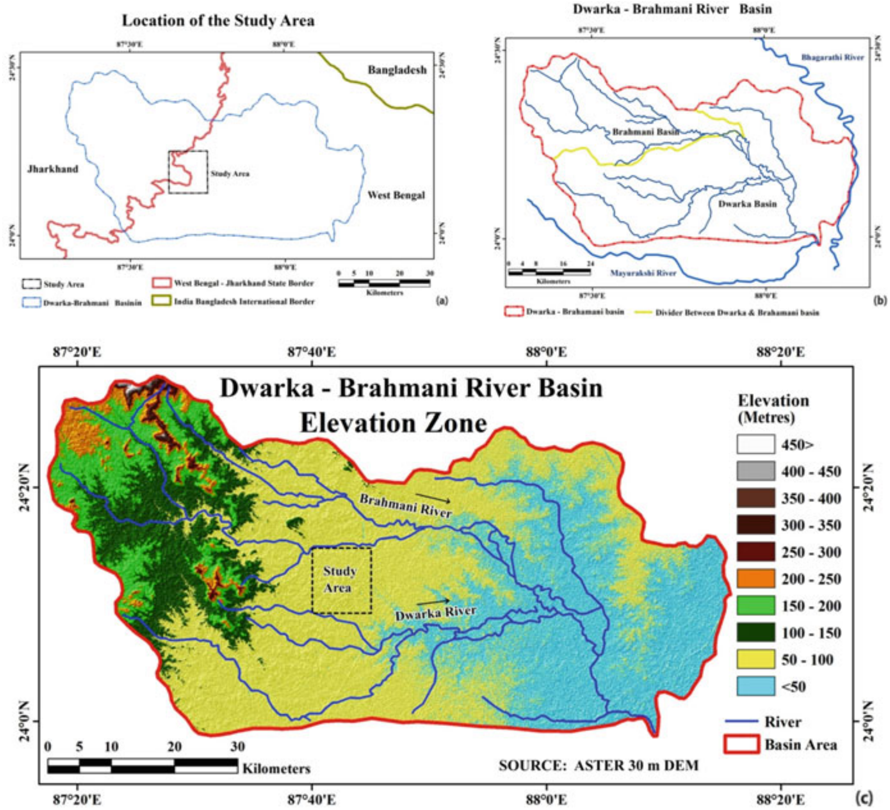


Fig. 7.2 Spatial extent and elevation zones of Dwarka-Brahmani Interfluve (Ghosh & Guchhait, 2020)

The climate of this region has been identified as sub-humid and sub-tropical monsoon type, receiving mean annual rainfall of 1300–1437 mm. The amount of rainfall is decreasing from western to eastern part. On the basis of 2010–2016 rainfall data, the mean annual rainfall of Paikor, Md. Bazar, Rampurhat and Mallarpur is 720.0 mm, 1176.0 mm, 1293.5 mm and 1372.8 mm respectively. The peak monsoon and cyclonic rainfall intensity of 21.51 mm h^{-1} (minimum) to 25.51 mm h^{-1} (maximum) are the most powerful climate factors to develop this lateritic badlands (Table 7.3) (Ghosh & Bhattacharya, 2012). The region has experienced intense thunderstorms during hot summer and prolonged rainfall during the tropical depression and cyclone.

In and around the study area, the soil series of Bhatina, Raspur and Jhinjharpur (Sarkar et al., 2007) has been developed in the present geo-climatic setting. Generally, thin solum is loamy skeletal and hypothermic in nature developing on the barren lateritic wastelands with sparse bushy vegetation and grass. The dark reddish to brown-coloured sandy clay loam of 0–16 cm (A horizon, maximum grass root

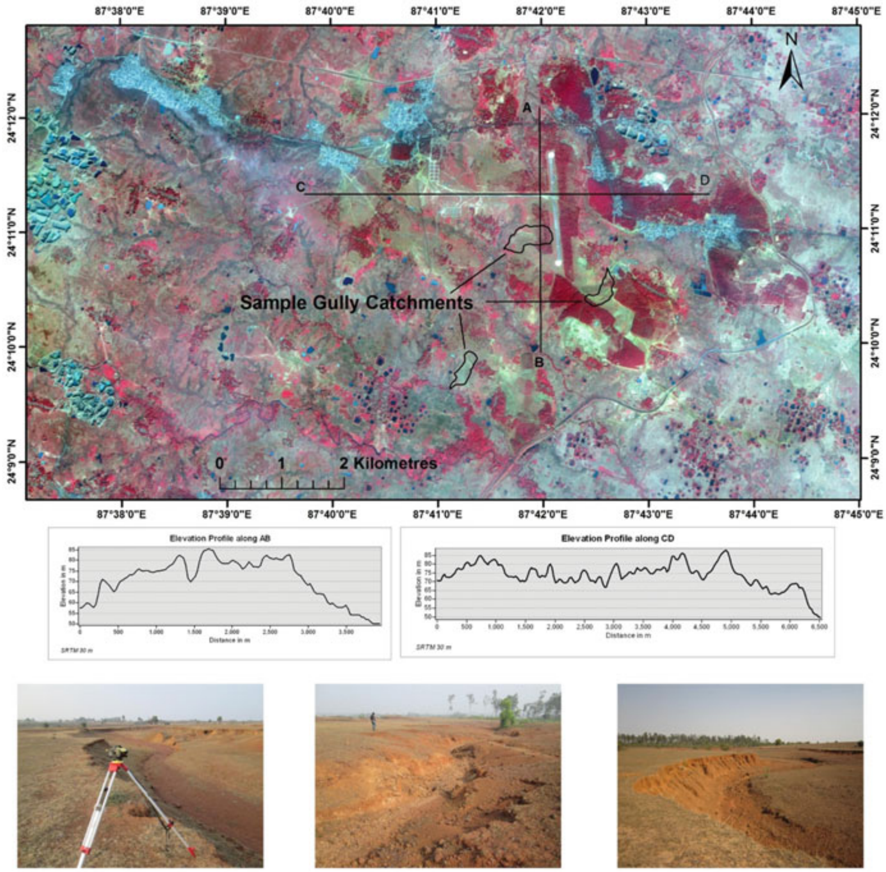


Fig. 7.3 Standard FCC IRS LISS IV image (Dec, 2015) of study area showing location of sample gully catchments, SRTM DEM elevation profiles and field photographs

Table 7.3 Climate–erosion relationship in the study area

Climatic phenomena	Effects on landforms and soil loss
1. Seasonal variation of temperature (about 15°–18 °C) and ground moisture	Encourage various processes of weathering, like block disintegration, formation of cracks and joints
2. High temperature range (max. 45 °C and min. 9 °C)	Lowering soil moisture and ground water table, loosening of soil particles, drying up of surface soils, reduction in soil cohesiveness
3. Season rainfall (from mid-June to October)	Weathered products and loose particles are removed from slope, favour lateritization
4. Short phase of heavy downpour within monsoon months	Development of badland topography, maximum erosion, tunnel erosion, mass wasting of valley sides and head cut migration of rill and gully

Source: Ghosh and Bhattacharya (2012)

Table 7.4 Estimated SCS-CN values of AMC II condition in the sample gully catchment 1, 2 and 3 on the basis of existing land use/land cover

Gully catchment 1						
HSG group	LULC	CN II	Area (m^2)	Product of CN II × area	CN II weighted	S (mm) II
C	Natural Vegetation	73	27,700	2,022,100	85.88	41.72
B	Grassland	86	41,150	3,538,900		
B	Bare surface	91	40,400	3,680,040		
Gully catchment 2						
HSG group	**LULC**	**CN II**	**Area (m^2)**	**Product of CN II × area**	**CN II weighted**	**S (mm) AMC II**
C	Natural Vegetation	73	25,900	1,890,700	85.52	42.97
B	Grassland	86	36,275	3,119,650		
B	Bare surface	91	56,150	5,109,650		
Gully catchment 3						
HSG group	**LULC**	**CN II**	**Area (m^2)**	**Product of CN II × area**	**CN II weighted**	**S (mm) AMC II**
C	Natural Vegetation	73	64,500	4,708,500	84.9644	44.92
B	Grassland	86	28,600	2,459,600		
B	Bare surface	91	122,950	11,188,450		

Note: *HSG* Hydrologic Soil Group, *LULC* land use/land cover, *CN* curve number, *S* maximum surface storage, *AMC* antecedent moisture condition
Source: Ghosh and Guchhait (2020)

zone) is developed over the fragmented secondary laterites. The loose secondary laterite (16–34 cm) is developed as cementation (low cohesion and weak structure) of derived materials over mottle and kaolinte horizon, and it is much prone to overland flow erosion, tunnel erosion and bank failure (Ghosh & Guchhait, 2020). The natural vegetation of the study area belongs to the tropical moist and dry deciduous type with few evergreen types. The observed natural vegetation species are Babul (*Acacia nilotica*), Bel (*Aegle marmelos*), Behara (*Terminalia bellirica*), Sal (*Shorea robusta*), Mahua (*Madhuca indica*), Khair (*Acacia catechu*), Khajur (*Phoenix sylvestris*), Jamun (*Syzygium cumini*), etc.

In this context, the land use classification and SCS-CN (Soil Conservation Service–Curve Number) data of three sample gully catchments are derived. In gully catchment 1 (basin area of 109,250 m^2), the principal land use/land cover is identified as natural vegetation (25.35%), grassland (37.67%) and bare laterite land (36.98%) (Table 7.4) (Ghosh & Guchhait, 2020). In gully catchment 2 (basin area of 118,325 m^2), the areal coverage of natural vegetation, grassland and bare laterite soil are 21.88%, 30.65% and 41.47%, respectively. In gully catchment 3 (basin area of 216,050 m^2), the total areal coverage of natural vegetation, grassland and bare laterite land are 29.85%, 13.23% and 56.94%, respectively (Ghosh & Guchhait, 2020). Applying the SCS-CN method (Chow et al., 1998; Mishra & Singh, 2003; Mishra et al., 2006; Bhunya et al., 2014; Gajbhiye et al., 2014; Srivastava & Imtiyaz, 2016; Singh, 2016) in three sample watersheds of gullies, it is found that on the basis of rainfall range of 42–137.2 mm, the sample watersheds can yield runoff of 40.02–118.0 mm in excess moisture condition of monsoon (Ghosh & Guchhait, 2020).

7.3 Methodology

The goal of United Nations Sustainable Development have new challenges and policy developments which provide opportunities for researchers and scholars to respond with more accurate assessments of erosion rates and solutions of erosion vulnerability, targeting negative trend of land degradation (Panagos & Katsoyiannis, 2019). To understand the hydro-geomorphic processes of soil erosion and to apply quantitative erosion models, the study demands an inter-disciplinary outlook, applying the methods of hydrology, geomorphology and statistics. The total methodology is combination of various sequential steps, viz. development of experimental design, data collection, model description, application and evaluation, soil loss tolerance, statistical analysis and thematic mapping (Fig. 7.4).

Experimental Design and Erosion Measurement at Hillslope Scale

The selection of erosion measurement sites to justify the application of erosion model poses a problem of sampling. Since it is not only possible to take measurements at each specific point in the landscape, it is important that the sample area should be representative of the catchment as high erosion prone zone (where maximum erosion is observed). From the field survey, it is observed that except permanent channels, the gully head slope (average slope 7°34′) is the key pathway of sediment transport to the main gully. In this lateritic terrain, the high erosion risk catchment of gully is firstly selected, and it has well-defined basin area (about 109,250–216,050 m^2) and dense network of gullies (7.57–8.33 km km^{-2}) (Fig. 7.5). Firstly, 18 gully heads of 3 basins (selected randomly within 17 basins at study area, based on high drainage density of greater than 7.5 km km^{-2}) were identified, and then 18 gully head slope elements (considering 2 m width of slope strip to incorporate soil–land use parameters) were selected, denoting S1–S18, respectively. The steepness of hillslope was measured using Leica Sprinter 150 m digital levelling instruments (accuracy – ± 0.7 mm of the 250 m distance) and other parameters of models were estimated in the recurrent field survey (2016–2018) and

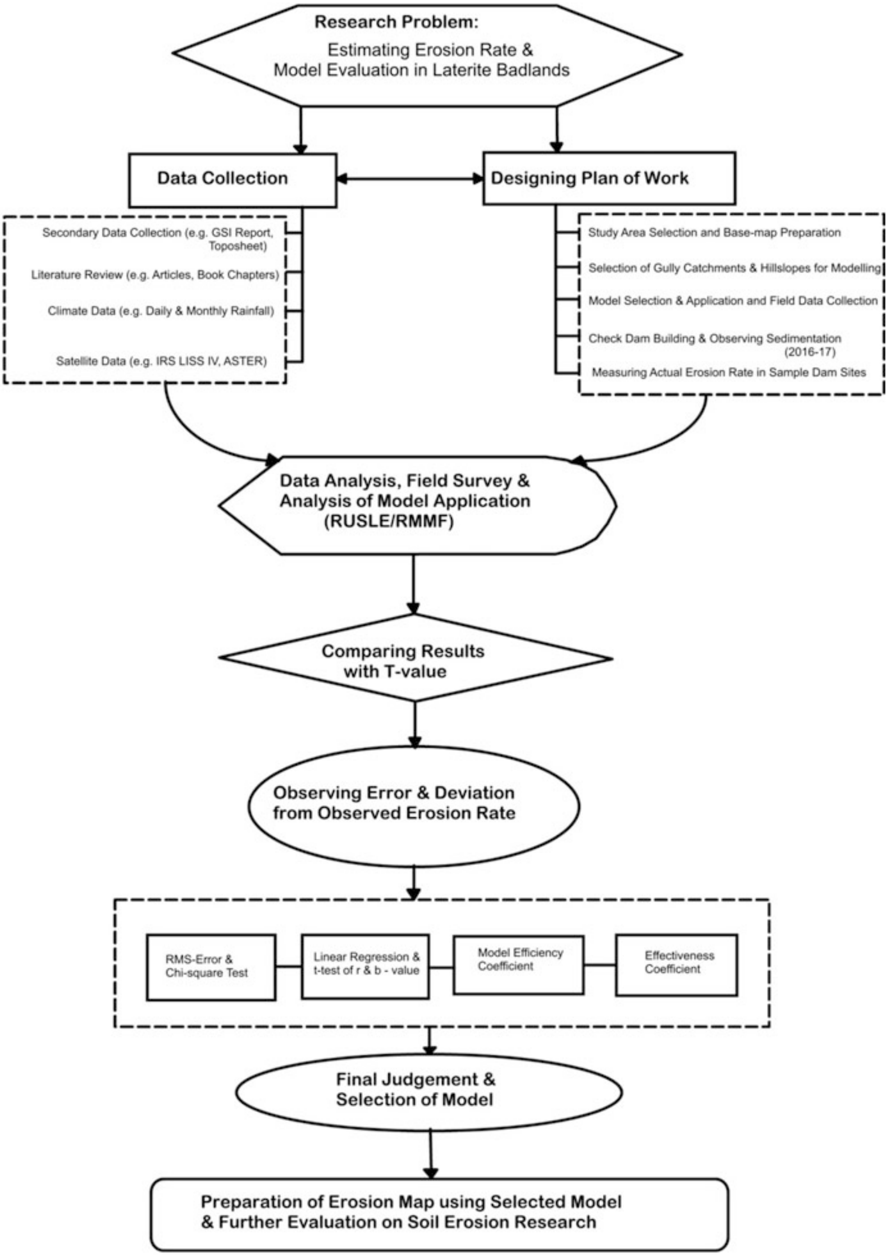


Fig. 7.4 Methodological flowchart of erosion model used in soil erosion research

Fig. 7.5 Experimental design for erosion modelling at hillslope scale in a lower order catchment: (**a**) selection of sample catchments and (**b**) selection of erosion plot and dam sites in a catchment

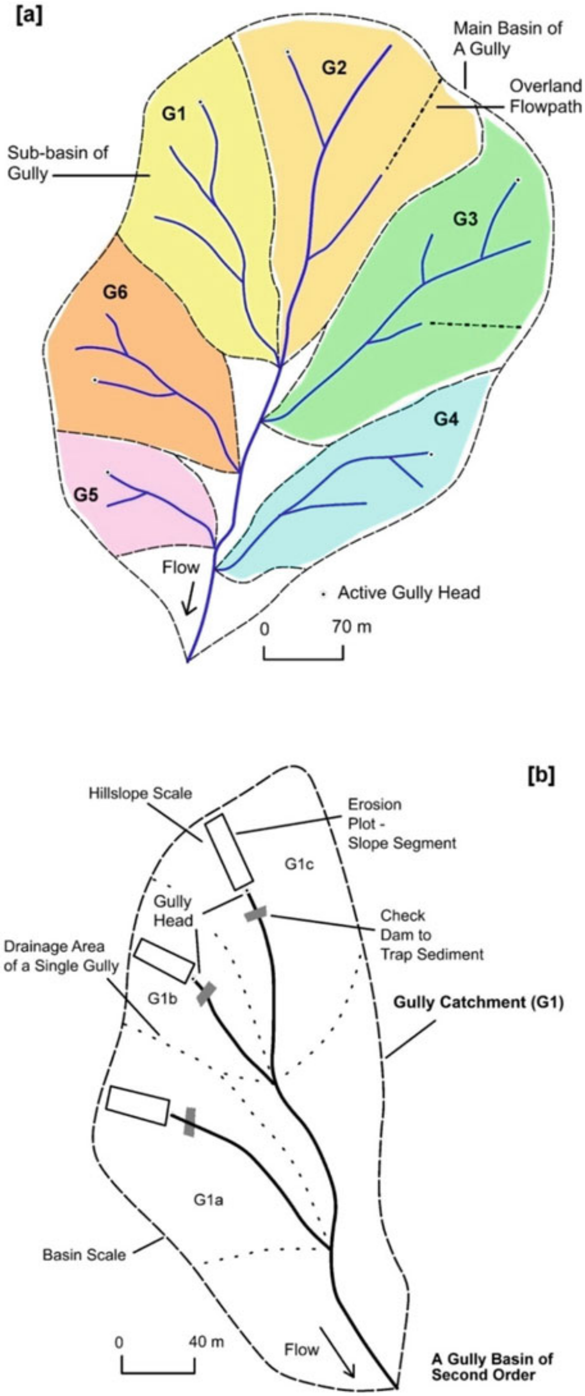


Fig. 7.6 (**a**) Sample dam locations at gully headcuts in catchment 1, (**b**) development of temporary dam to trap sediments, (**c**) final structure of small dams below gully headcuts and (**d**) measuring the morphological parameters above dam

guided values of erosion models (Renard et al., 2011; Renard et al., 1997; Morgan, 2001; Morgan & Duzant, 2008). The total slope length is the overland flow part between the gully head and water divide. The steepness of slope elements varies from 3°45′to 11°06′, whereas slope length varies from 22.1 m to 106.8 m. Maintaining a certain distance (1.5 to 2 m) from active gully head, 18 check dams (used as sedimentation pits) were developed (denoting Dam 1 to Dam 18) at the base (i.e. gully floor) of representative slope elements to trap eroded sediments coming from upslope in a year (2016–2017) (Fig. 7.6).

Following the shape of gully channel, it was decided to built *V*-shape design using sand, cement and laterite boulders of irregular shape, and the gap between gully head base and dam was used as sedimentation pits to collect eroded materials. The dams were developed in January 2016 with the help of local manpower and resources. The constructed dams had a height range of 40–55 cm and width range of

92–190 cm. Mostly during monsoon period (June to October) of 2016, the eroded material of these slope elements or upstream drainage areas of gullies were trapped behind the dams. It is very needed to mention that occasional high sediment flux was observed during few extreme thunderstorms (5 times in 2016), having very high rainfall intensity of greater than 25.51 mm h^{-1} (April to June). Then after one year of observation, the sedimentation was measured in January 2017, and the mass volume was measured as multiplying the area of sedimentation behind dam and mean depth of sedimentation at 18 dam sites. The bulk density of eroded materials was calculated at laboratory (mean bulk density of materials is 1.717 gm cm^{-3}), and the mass weight of sedimentation materials was measured by multiplying the volume of mass (unit in kg) by bulk density. The observed rate of erosion (unit as kg m^{-2} $year^{-1}$) was measured by dividing the mass weight by strip area of slope element or erosion plot for one year (2016–2017).

It was calculated that in 18 dam sites, the estimated weight of trapped sediments (i.e. mostly ferruginous nodules and coarse sands) varies to a great extent due to activeness of water erosion, slope angle and overland flow length, ranging from 566 to 3581 kg. The observed annual erosion rate (O) of three sample catchments was finally measured as (a) 10.50–24.27 kg m^{-2} $year^{-1}$ (gully catchment 1), (b) 8.12–20.82 kg m^{-2} $year^{-1}$ (gully catchment 2) and (c) 11.87–20.82 kg m^{-2} $year^{-1}$ (gully catchment 3), respectively (Table 7.5). The average observed rate is near about 16.27 kg m^{-2} $year^{-1}$ which is much greater than the soil loss tolerance T-value of this region (i.e. 1.0 kg m^{-2} $year^{-1}$). Field survey and laboratory analysis suggest that erosion occurs on two types of soil texture—(1) sandy loam and (2) sandy clay loam (Table 7.6). Therefore, it can be said that the lateritic badlands of study area have high erosion risk (rendering organic rich top-soil development and increasing Fe-crusting, badlands area and degradation of biomass) and the region needs immediate protective measures to check erosion and land degradation at basin scale. After getting the measured erosion data, the analysis was carrying forward to fulfill the key purpose of study which was to compare the predicted data of erosion models (RUSLE and RMMF) with the observed data at field scale.

Secondary Data Collection

The key sources of main secondary data are regional soil report, geology report and other physical environmental report published by NBSS and LUP (National Bureau of Soil Service and Land Use Planning), Census of India, district gazetteer, official websites of IMD (Indian Meterological Department) Pune and Kolkata, Irrigation and Waterways Dept. of Govt. of West Bengal (IWD), Geological Survey of India (GSI), related e-books and e-journals. The topographical sheets of Survey of India (72 P/12/NE, R.F. 1:25,000 and 72 P/12, R.F. 1:50,000), District Resource Map of Geological Survey of India, District Planning Map of NATMO (National Atlas Thematic Mapping Organization) and Block map of Census of India are most important sources of spatial information (Ghosh & Guchhait, 2020). Landsat TM

Table 7.5 A brief summary of dam's parameters, sedimentation and observed rate of water erosion at 18 dam sites of three catchments (year of observation 2017–2018)

Gully catchments	Check dam	Width (cm)	Height (cm)	Mean sedimentation depth (m)	Measured mass of sediment (kg)	Rate of erosion kg m^{-2} $year^{-1}$ [mean = 16.27 kg m^{-2} $year^{-1}$]
Catchment 1	1	102	42	0.13	0566	14.10
	2	110	50	0.20	614	19.94
	3	87	41	0.25	2204	24.27
	4	114	48	0.15	1881	14.45
	5	98	35	0.11	1068	10.50
	6	94	30	0.23	3583	24.01
Catchment 2	7	98	37	0.22	0713	8.12
	8	110	41	0.27	3350	15.81
	9	108	46	0.15	2798	15.23
	10	122	48	0.11	1741	10.15
	11	107	45	0.19	1458	20.82
	12	125	51	0.23	2428	14.71
Catchment 3	13	98	32	0.19	2258	15.05
	14	105	45	0.23	1774	16.12
	15	102	48	0.27	2579	19.24
	16	112	54	0.14	2137	11.87
	17	94	40	0.17	2598	20.62
	18	90	38	0.20	1977	17.97

Table 7.6 Textural data of sample soils in the study area

Sample site	Location	Sand %	Silt %	Clay %	Organic matter %	Soil texture
1	24°11′06″N, 87°42′40″E	65.3	24.6	10.1	0.61	Sandy loam
2	24°10′57″N, 87°42′49″E	64.0	22.4	13.6	0.68	Sandy loam
3	24°11′23″N, 87°42′40″E	52.6	28.3	19.1	0.21	Sandy clay loam
4	24°11′51″N, 87°42′41″E	70.2	19.1	10.7	0.57	Sandy loam

and ETM+ (30 m resolution) images are downloaded from the website of Global Land Cove Facility (GLCF) and SRTM (Shuttle Radar Topography Mission, 90 m resolution), and ASTER (*Advanced Spaceborne Thermal Emission and Reflection* Radiometer, 30 m resolution) elevation data are downloaded from the websites of GLCF and Consortium for Spatial Information (CGIAR-CSI) (Ghosh & Guchhait, 2020). The spatial information is stored in Geographic Information System (GIS) and the thematic maps are prepared using GIS software (ArcGIS 9.2 and Erdas Image 9.1) (Ghosh & Guchhait, 2020).

In this case we have gathered the daily, monthly and annual rainfall data from three IWD (Irrigation and Waterways Department, Government of Wes Bengal) rain-gauge stations at Nalhati (24°17′25″N, 87°49′44″E), Rampurhat (24°10′13″N, 87°46′50″E) and Mollarpur (24°04′35″N, 87°42′36″E) which are situated at eastern part of study area, having areal distance of 18–25 km. The calculated mean annual rainfall for this region is 1510 mm in 2016 (maximum intensity of erosive rain is 25.21 mm h^{-1}), and the per day rainfall amount is 17.48 mm, considering total rainfall and rainy days in a year.

The base map is geo-referenced in UTM (Universal Transverse Mercator) projection with WGS-84 (World Geodetic Survey, 1984) datum. In the GIS framework, we have plotted the existing drainage of study area (derived from toposheet) on the ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) elevation map to depict the regional dissection of water divides (Ghosh & Guchhait, 2016). The locations of laterite exposures are mapped on the basis of field expeditions, toposheets, survey points of Garmin Montana 650 GPS receiver (with horizontal accuracy of ±3 m) and Google Earth Pro. Leica Geosystem Sprinter 150 m was used to measure the angle of slope facets (Ghosh & Guchhait, 2016). Alongside few cases (due to physical obstacles) from ASTER DEM (Digital Elevation Model), the slope length and angle (usually from gully headcut to water divide) is measured to judge the length of surface flow (responsible for gully erosion) (Ghosh & Guchhait, 2016).

Potential and Problem of Erosion Models

Models are of necessary simplifications of reality (Morgan, 2005). Researchers seek models that describe how the system functions in order to enlighten understanding of the system and how it responds to change (Morgan, 2005). It is not possible to take measurements at every point in the landscape, and it also takes time to build up a sufficient database and long-term measurements (Morgan, 2005). In order to overcome these deficiencies, models can be used to predict erosion under a wide range of conditions. Erosion models can be used as predictive tools for assessing soil loss for conservation planning, project planning and soil erosion inventories and for regulation, and it can be used a tools for understanding erosion processes and their interactions and for setting research priorities (Nearing et al., 1994). In selecting an erosion model, a rational decision must be made as to whether the model is to be used for on-site concerns (degradation of thinning of the soil profile) or off-site concerns (sediment yield or siltation of reservoirs) (Nearing, 2013).

The mathematical equations used in erosion models have five components: (1) independent variables, (2) dependent variables, (3) parameters, (4) mathematical operators and (5) a computation sequence and logic that link the equations within the model (Toy et al., 2013). The three major types of erosion models based on model structure are the regression-derived, index-based and process-based models (Table 7.7). One was to derive an erosion model that uses statistical regression procedures to fit an equation to a data set. The equation form and independent variables (factors) in the equation are selected to give the best fit to the experimental data as measured by a statistical goodness of fit (Toy et al., 2013). Every erosion model must represent how the four factors of climate, soil, topography and land use

Table 7.7 A short description of erosion models

Model type	Form	Derivation method	Strengths
Regression-derived	A single or a few equations having a for that best fits the data	Derived by fitting an equation(s) to an empirical database representing field conditions	Generally simple and easy to use; input values can be simple and easy to obtain
Index-based	Using indices, usually in a multiplicative form, to represent how climate, soil, topography and land use affect erosion	Values for indices determined from large empirical database representing field conditions	Simple and easy to use; input values can be simple and easy to obtain; very powerful in relation to simplicity and input values
Process-based	Represents individual erosion processes using simple steady-state equations	Equations derived from theory and empirical databases for erosion processes, validated against database representative of field conditions	Can be simple; represents main fundamental erosion processes; improved performance

affect soil loss and related variables (Toy et al., 2013). Toy et al. (2013) have suggested a simple form of erosion as follows (Eq. 7.1):

$$SL = CF.SF.TF.LUF \tag{7.1}$$

where SL = average annual soil loss, CF = climate factor, SF = soil factor, TF = topographic factor and LUF = land use factor.

Equation (7.1) is an index-based erosion model. Each variable in the equation is an index that represents the effect of that variable based on the value assigned to the index. In process-based or dynamic models, erosion occurs as a series of discrete events with different erosion amounts for each event because of differences in storms and land use conditions at each event (Toy et al., 2013). These models can track temporal variables by computing values at regular points through time between storm events. The physically based erosion models and regression models have until now not always provided very satisfying results for prediction of soil erosion and sediment yield (Poesen, 2018).

Problems of Using Models and Its Solution

It is found that lumped parameter models (i.e. empirical models) linked to GIS are practicable for conservation planning than sophisticated distributed parameter models. Lumped Parameter Models (LPMs) use averaging techniques to lump the influence of non-uniform spatial processes of a given area, such as a basin-averaged precipitation for run off computation (Torri & Borselli, (2012); Avwunudiogba & Hudson, 2014). The RUSLE is an empirical equation for predicting long-term average soil erosion from agricultural field under specific cropping and management practice. There are few hindrances or problems to implement distributed parameter or process-based models (like WEPP, EURSOEM etc.) in the study area. Three key problems are stated as follows (Boardman & Favis-Mortlock, 1998; Morgan and Nearing, (2011)):

(1) Does the amount of money and time devoted to collection of the data justify their application for simple watershed planning in humid tropical environments?
(2) Do communities in these region possess the institutional framework, personnel and financial commitment to undertake the long-term research necessary for implementations of process-based models?
(3) LPMs are more attractive in the immediate future because of the ease with which data requirements can be met and the greater suitability of these models for the socio-economic context of this region.

The models can be implemented in situations with limited data and parameter inputs and are particularly useful as a first step in identifying sources of sediment and nutrient generation (Merriti et al., 2003). Empirical models or index-based models are based primarily on the analysis of observations and seek to characterize response from the data. The feature of this class of models is their high level of spatial and temporal aggregation and their incorporation of a small number of casual variables (Merriti et al., 2003). In this study, an index-based model (Revised Universal Soil Equation, RUSLE) and a combined index-based and process-based model (Revised Morgan Morgan Finney model, RMMF) are applied to get predicated erosion rates, and then two models are compared to evaluate the suitability and effectiveness of each model in the erosion prone region of laterite terrain. The total workflow of erosion model selection, processing, application and analysis are completed in seven steps—(1) user requirements, (2) model selection, (3) developing core database, (4) expanding database, (5) model verification, (6) validating the model and (7) sensitivity analysis (Boardman & Favis-Mortlock, 1998; Nearing, 2013; Morgan, 2005; Morgan and Nearing, 2011; Toy et al., 2013).

Revised Universal Soil Loss Equation (RUSLE)

One of the main reasons why RUSLE type modelling is so widely used throughout the world is certainly its high degree of flexibility and data accessibility, a parsimonious parameterization, extensive scientific literature and comparability of results allowing to adapt the model to nearly every wind of condition and region of the world (Alewell et al., 2019). The precise description of RUSLE is found in the writing of Renard et al. (1997), predicting soil erosion by water for conservation planning in the geo-climatic condition of the USA. Chandramohan et al. (2015) have applied RUSLE, Unit Sediment Graph (USG) and Water Erosion Predication Project (WEPP) on small watersheds of Pamba River Basin (Kerala, India) to observe rainfall–runoff–sediment yield relationship, and they have found good applicability of RUSLE than other models. Similarly, Smith (1999), Sovrin (2003), Babu et al. (2004), Martin-Fernandez and Martinez-Nunez (2011), Jain and Das (2012), Sinha et al., (2012), Sinha and Joshi (2012), Bayramov et al. (2013), Kinnell (2014), Karydas et al. (2014), Devatha et al. (2015), Mondal et al. (2017) and Benavidez et al. (2018) have successfully applied RUSLE to assess erosion rate in different environmental settings, and they have found the suitability and effectiveness of RUSLE in comparison to other models, e.g. Soil Loss Estimation Model for Southern Africa (SLEMSA), Morgan Morgan Finney Model (MMF), Water Erosion Prediction Project (WEPP) and European Soil Erosion Model (EUROSEM). The applied version of RUSLE (Eq. 7.2) is mentioned as follows (Renard et al., 1997) (Table 7.8 and Fig. 7.7):

$$A = R\,K\,L\,S\,C\,P \tag{7.2}$$

where

- A is the computed soil loss per unit area (tons per acre per year); it can transformed into SI unit

Table 7.8 Operating parameters and functions of the RUSLE model

Description	Operating functions	Parameter definitions	Source
Rainfall Erosivity Index (R)	$R = (R_1 + R_2)/2$ $R_1 = P$ $(0.119 + 0.0873 \log_{10} I_m). \log_{10} I_{30}$ $R_2 = 79 + 0.363\ P$	P is the mean annual rainfall, I_m is the average rainfall intensity (i.e. 25.21 mm h^{-1}), I_{30} is the maximum 30 min rainfall intensity (i.e. 75 mm h^{-1}, recommended by Wischmeier & Smith, 1978)	Renard et al. (1997); Sarkar et al. (2005); Jha and Paudel (2010); Ganasri and Ramesh (2016); Benavidez et al. (2018)
Soil Erodibility Index (K)	$K = 1.2917$ $[2.1 \times 10^{-4}\ (12 - \mathrm{OM})\ M^{1.14} + 3.25\ (s - 2) + 2.5\ (p - 3)]/100$ $M = \%$ silt $(100 - \%$ clay)	OM is the percentage of organic matter in soil, M is the particle size parameter, s is the soil structure code and p is permeability code recommended by (Wischmeier &and Smith, 1978)	Sarkar et al. (2005); Bayramov et al. (2013)
Slope-Length Index (LS)	$\mathrm{LS} = (L/22.13)^{0.5}.\ (0.065 + 0.045\ \theta + 0.0065\ \theta^2)$	L is the slope length (m) and θ is slope steepness in percent	Sarkar et al. (2005); Rahaman et al. (2015)

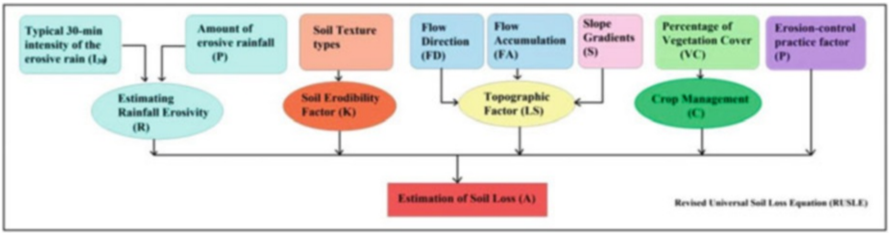


Fig. 7.7 Flowchart of data input and methods for RUSLE-based soil erosion modelling

- R, the rainfall and runoff factor, is the number of rainfall erosion index units, i.e. EI_{30}
- K, the soil erodibility factor, is the soil loss rate per erosion index unit for a specified soil as measured on a unit plot, which defined as a 72.6 ft length of uniform 9% slope continuously in clean-tilled fallow
- L, the slope-length factor, is the ratio of soil loss from the field slope length to that from a 72.6 ft length under identical conditions
- S, the slope-steepness factor, is the ratio of soil loss from the field slope gradient to that from a 9% slope under otherwise identical conditions
- C, the cover and management factor, is the ratio of soil loss from an area with specified cover and management to that from an identical area in tilled continuous fallow

- P, the support practice factor, is the ratio of soil loss with a support practice like contouring, strip cropping or terracing to that with straight-row farming up and down the slope

Revised Morgan–Morgan–Finney (RMMF) Model

Another popular model is the revised Morgan–Morgan–Finney (RMMF) model which was documented in the article of Morgan (2001), and its modifications were done by Morgan and Duzant (2008) to enable the effects of vegetation cover to be expressed through plant parameters. This model is also effectively applied in a variety of geo-climatic conditions (Sovrin, 2003; Mondal et al., 2011; Bayramov et al., 2013; Avwunudiogba & Hudson, 2014; Tesfahunegn et al., 2014; Efthimiou, 2019), and many workers (Jetten et al., 1994; Vente & Poesen, 2005; James et al., 2017; Choi et al., 2017) have given the results of model evaluation and additional modifications for the development and further applicability of RMMF model. The model validation was carried out by comparing predicted and observed values of annual runoff and erosion for 67 sites in 12 countries (Morgan et al., 1984). The model comprises a water phase and a sediment phase. Rainfall energy and runoff volume are estimated from annual rainfall amount in the water phase (Morgan et al., 1984; Morgan, 1986). In the sediment phase, erosion is taken to result from the detachment of soil particles by rainsplash and their transport by runoff (Morgan et al., 1984; Morgan, 1986). The revised version of the model is depicted as follows (Morgan, 2005) (Table 7.9 and Fig. 7.8).

Sensitivity Analysis

Two types of sensitivity indices are used in this study (Eq. 7.3): (a) Absolute Sensitivity (AS) and (b) Average Linear Sensitivity (ALS) (Nearing et al., 1989). The absolute sensitivity describes the rate of change in output with respect to a change in the value of input. The relative sensitivity describes the normalization of input and output in relation to their mean values, to produce an average linear sensitivity index. Now, ALS is widely popular in erosion prediction technology, and it can be described as follows (Morgan, 2005):

$$\mathrm{ALS} = [(O_2 - O_1)/O_\mathrm{m}]/[(I_2 - I_1)/I_\mathrm{m}] \tag{7.3}$$

where O_1 and O_2 are values of model output obtained with values of I_1 and I_2 of input and O_m and I_m represent the respective average values of the two input and output values. If ALS is greater than 1.0, then the input parameter is highly sensitive to change in output. Alongside the estimated error between (Eq. 7.4) measured and

Table 7.9 Operating parameters and functions of the RMMF model

Description	Operating functions	Parameter definitions	Source
Effective Rainfall (ER, mm)	ER $= R_a (1 - A_c)$	R_a = mean annual rainfall (mm); A_c = proportion of rainfall reaching soil surface considering canopy cover (0 to 1) in the basin	Morgan (2005); Morgan and Duzant (2008); Efthimiou (2019)
Leaf Drainage (LD, mm) and Direct throughfall (DT, mm)	LD = (ER − CC), DT = (ER − LD)	CC = proportion of canopy cover (0 to 1)	
Kinetic energy of LD (KE $_{LD}$, J m^{-2})	KE_{LD} = LD [(15.8 − $P_H^{0.5}$) − 5.87]	P_H = plant height (m)	
Kinetic energy of DT (KE $_{DT}$, J m^{-2})	KE $_{DT}$ = DT (11.9 + 8.7 log I)	I = erosive rainfall intensity (mm h^{-1})	
Total kinetic energy (KE_T, J m^{-2})	$KE_T = KE_{LD}$ + KE $_{DT}$	–	
Soil moisture storage capacity (R_C)	R_C = 1000.MS.BD. EHD.(E_t/E_o)	MS = soil moisture content at field capacity (% w/w); BD = bulk density of soil (Mg m^{-3}); effective hydrological EHD = effective hydrological depth (m); E_t/E_o = the ratio of actual to potential evapotranspiration	
Annual Runoff (I_r, mm)	Q_r = ER. exp ($-R_c/R_o$)	I_o = mean daily rainfall (mm)	
Annual soil particle detachment by raindrop impact (F, kg m^{-2})	$F = K$. KE .10^{-3}	K = soil erodibility (g J^{-1})	
Annual soil particle detachment by runoff (H, kg m^{-2})	H = ZQ$^{1.5}$ sin S (1-GC) 10^{-3} Z = 1/0.5 COH	S = slope steepness; GC = proportion of ground cover (0–1); Z = resistance of soil; COH = soil cohesion (kPa)	
Total detachment (J, kg m^{-2})	$J = H + Z$	–	
Annual transport capacity of runoff (G, kg m^{-2})	$G = C\,Q^2 \sin S.10^{-3}$	I = the product of the C and P factors of RUSLE	

predicted values, it can be calculated by root mean square relative error (RMS-error) using the following equation (Morgan, 2005).

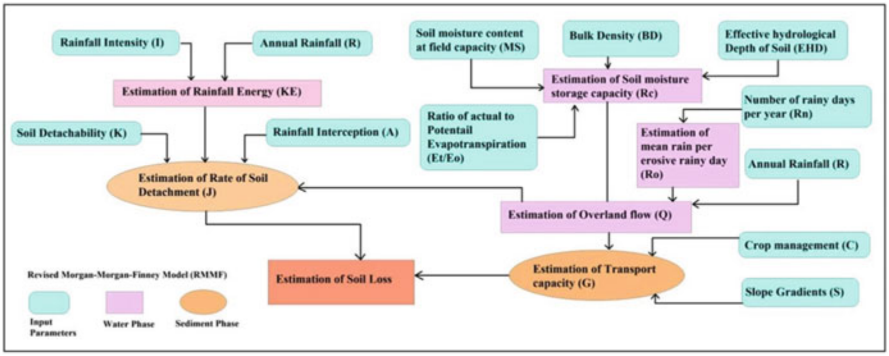


Fig. 7.8 Flowchart of data input and methods for RMMF-based soil erosion modelling

$$\mathrm{RMS-error} = \sqrt{\left[{}_{i=1}\Sigma\left(\mathrm{X_{obs}} - \mathrm{X_{pred}}\right)^2 100/\mathrm{m}\right]} \tag{7.4}$$

where *m* is the number of observations.

Model Validation

Validation is the process of ensuring that the model serves its intended purpose as described in the user requirements (Morgan, 2005; Toy et al., 2013), although an important part of validation is to determine how well the model fits measured data. Erosion models typically fit measured average annual soil loss with an uncertainty of about ±25% for moderate erosion rates of about 6–60 metric tons per hectare per year (Toy et al., 2013). The model efficiency coefficient (MEC), firstly proposed by Nash and Sutcliffe (1970), is now increasingly used an alternative to the correlation coefficient to express the performance of model (Morgan, 2011). Generally, a MEC value (Eq. 7.5) of greater than 0.5 is considered that the model performs satisfactorily in the region, and one should not expect values to exceed 0.7 (Quinton & Morgan, 1998; Morgan, 2005, 2011).

$$\mathrm{MEC} = 1 - \Sigma\left(X_{\mathrm{obs}} - X_{\mathrm{pred}}\right)^2 / \Sigma\left(X_{\mathrm{obs}} - X'_{\mathrm{obs}}\right)^2 \tag{7.5}$$

where X_{obs} is the observed value, X_{pred} is the value predicted by the model and X'_{obs} is the mean of a set of observed values.

One of the important methods used to evaluate the effectiveness of soil erosion model is to compare the predictions given by the model to measured data from soil loss collected on plots taken under natural rainfall conditions (Nearing, 2013). A model 'effectiveness coefficient' was defined by Nearing (2013) for studies undertaken on large numbers of prediction versus measured data comparisons. This method provides a quantitative criterion for taking into account natural variability and uncertainty in measured erosion plot data when those data are used to evaluate erosion models (Nearing, 2013). Null hypothesis is that RUSLE or RMMF prediction (P_s) is equal to the measured value (M) for that case.

$$\text{Null hypothesis—}H_0 : P_s - M = 0$$

$$\text{Alternative hypothesis—}H_1 : P_s - M \neq 0$$

The relative difference (R_{diff}) between predicated and measured values (Eqs. 7.6 and 7.7) are calculated and then a particular set of conditions that 95% of the values for differences in erosion (fall within a certain range) is calculated.

$$R_{diff} = (P_s - M)/(P_s + M) \tag{7.6}$$

Relative difference values (Y-axis) are plotted against measured values (X-axis) to get a trend in the scatters.

$$R_{diff} = m \log_{10}(M) + b \tag{7.7}$$

The method of evaluation of a single data point may be extended to the larger data set and, from the analysis a model effectiveness coefficient (E_c), may be calculated. It is defined E_c as the fraction of simulation model predictions for which a model is effective in predicting the measured erosion, using the acceptance criteria. Using the 95% occurrence intervals from the replicated erosion data, it would result in a value, $E_{c(a=0.05)}$. The value of $E_{c(a=0.05)}$ signifies that the percentage of the difference between measured and predicted soil loss fell within the expected range of difference for two measured data points within the same population (Nearing, 2013). The procedure was as follows:

(1) List the measured and predicted data pairs.
(2) Calculate the relative difference between measured and predicted soil loss (R_{diff}).
(3) Compute the 95% occurrence interval as given by equation for each data point.
(4) Determine the number of predictions for which the R_{diff} value fell within the interval.
(5) Calculate $E_{c(a=0.05)}$ as the fraction of 'acceptable' predictions for the data set.

Statistical Analysis

For the statistical judgement and significant interrelationship of observed and predicted values, Chi-square test, linear regression, Pearson's product moment correlation, *t*-test of correlation and regression slope are applied (Table 7.10). χ^2 goodness of fit is used to determine where there is a statistically significant difference between expected frequencies and observed frequencies in sample population. The *p*-value of χ^2 test is also used to help us on the decision of rejection or acceptance of null hypothesis. The simple linear regression ($Y_c = a + bX$) and scatter plot gives an actual picture and trend of *X*-*Y* relationship which reflects the resemblance or

Table 7.10 Statistical parameter used in the study

Statistical parameter	Description and operating functions	Statements of null (H_0)/alternate (H_1) hypothesis
Chi-square test (χ^2 goodness of fit)	$\boldsymbol{\chi^2 = \Sigma\,(O_i - E_i)/E_i}$, $n - 1$ degree of freedom O_i = observed erosion rate, E_i = predicted erosion rate of RUSLE or RMMF	H_0 ($O_i - E_i = 0$)—no difference between observed and predicted erosion rate H_1 ($O_i - E_i \neq 0$)—significant difference between observed and predicted erosion rate
Linear regression	$\boldsymbol{Yc = a + b\,X}$ Y_c = predicted erosion rate of RUSLE or RMMF X = observed erosion rate a = intercept b = slope R^2 = coefficient of determination	–
Pearson's product moment correlation (r)	$\boldsymbol{r = \mathrm{Cov}(X, Y)/\sigma_X\,\sigma_Y}$ Cov (X, Y) = Covariance of X and Y σ_X = standard deviation of X σ_Y = standard deviation of Y Range = +1 < $\boldsymbol{r}$ < −1	–
t-test of b-value	$\boldsymbol{t_b = b/SE_b}$ SE_b = standard error of b $SE_b = \sigma_X/\sigma_Y \sqrt{}\,(1 - r^n)/(n - 2)$ n = number of sample degree of freedom ($n - 2$)	H_0—regression slope (based on observed and predicted erosion rate) is significant, having close resemblance of X–Y relationship H_1—slope is insignificant
t-test of r-value	$\boldsymbol{t_r = r\sqrt{}\,(n - 2)/(1 - r)}$ degree of freedom ($n - 2$)	H_0—there is a zero correlation H_1—there is a significant correlation, i.e. no zero
Confidence interval	$\boldsymbol{C_i = X_m \pm (Z.\ \sigma_X/\sqrt{n})}$ X_m = mean of observed erosion rates Z = the Z value (1.96) for desired confidence level α ($\alpha_{0.05}$–95% confidence level) (obtained from normal curve)	–

association between observed and predicted erosion rates. The b-value (slope of trend line) reflects the amplitude of trend line to understand the interdependence of predicted values on the observed values. In addition correlation coefficient value (r) also confirms the degree of resemblance in the X-Y relationship. Then the estimated values of b and r are tested using t-test statistics at 0.05 significance level.

Soil Loss Tolerance

The term 'soil loss tolerance' (T value) denotes the maximum level of soil erosion that will permit a high level of crop productivity to be sustained economically and indefinitely (Wischmeier & Smith, 1978). The soil loss tolerance value (i.e. T value) has been defined as indication of how much erosion should be tolerated (Osman, 2014). For example, shallow soils over hard rock terrain have small T values. The concept of T value mainly described the maximum acceptable soil loss allowing a high level of productivity to be maintained for a long period, based on consideration of soil fertility and productivity (Li et al., 2009). A value for the rate of erosion alone is, however, of limited use without a corresponding value for an 'acceptable' or 'tolerable' rate (T-value) of erosion. Rates of tolerable soil loss calculated using soil production rates range from 0.2 to 2.2 t ha^{-1} year^{-1} and tolerable rates based on maintenance of crop production range from approximately 1 to 11 t ha^{-1} year^{-1} (Pennock, 2019). The low T value reflects likelihood of rill and gully formation and loss of plant nutrients by erosion. Here, the T-value is compared with the results of experiment to understand the erosion risk.

7.4 Results

Analysis of RUSLE Results

The input parameters of RUSLE are mean annual rainfall (P); average rainfall intensity (I_m); soil erodibility (K) based on soil organic matter content and percentage of sand, silt and clay particles; crop cover and management factor (C); and protective erosion control factor (P). Based on average rainfall data of three rain-gauge stations (collected from Irrigation and Waterways Department, Government of West Bengal), the mean P is estimated as 1510 mm in 2016–2017, and I_m is calculated as 25.52 mm h^{-1} for this climatic region. The analysis has assigned the Rainfall erosivity factor (R) of RUSLE modelling, i.e. 654 for this region. The mean K-factor of laterite terrain is estimated by soil texture and organic matter content of sample soils and the average K values of the catchments varies from 0.23 to 0.28 (Table 7.11). In general, coarse granular soil structure ($b = 7$) and moderate soil permeability ($c = 3$) are observed on the ferruginous soils. The length of slope elements or erosion plots varies from 22.1 to 106.8 m (length in between gully head and water divide), having 55–75% of bare lateritic stony surface with development of rills. The steepness of hillslope varies from 3° 45′ to 11° 06′, having average slope of 7° 14′ 30″ in the sample sites. It is observed that the land use/land cover of the catchments do not change too much throughout the year, and the region has minimum human disturbance. The C-factor is estimated as weighted value in respect of land use condition in three gully catchments, and it varies in each slope elements—(1) 0.61–0.91 (gully catchment 1), (2) 0.65–0.83 (gully catchment 2) and (3) 0.68–0.82 (gully catchment 3). The most important phenomenon is that the study area is not protected under any erosive control measures, except few patches of Acacia plantation. Therefore, in each slope element, the P-factor is regarded as 0.1 for RUSLE modelling.

Based on the above estimation of inputs, multiplied R, K, LS, C and P factors are taken to get potential or predicated values of annual soil erosion rate (A_P). A_P of three gully catchments are estimated as (1) 13.22–20.87 kg m^{-2} year^{-1} (gully

Table 7.11 Input parameters sand predicted erosion rate of RUSLE model

Gully catchments	Check Dam	Slope length (m)	Slope degree	Gradient/steepness in percent	LS	K	R	P	C	A_P kg m^{-2} year^{-1} (mean = 16.633 kg m^{-2} year^{-1})
Catchment 1	1	22.1	10° 09′	11.27	1.33	0.28	654	0.1	0.61–0.91	15.89
	2	25.4	11° 06′	12.33	1.34					16.74
	3	45.4	8° 30′	9.44	1.53					18.7
	4	65	6° 11′	6.85	1.16					13.22
	5	74.5	5° 50′	6.63	1.19					13.07
	6	50.8	8° 05′	8.89	1.5					20.87
Catchment 2	7	44.2	4° 30′	5.2	0.67	0.23	654	0.1	0.65–0.83	7.86
	8	106.8	5° 30′	6.2	1.3					15.37
	9	84	7° 20′	8.15	1.68					19.71
	10	86.7	3° 45′	4.16	0.72					8.44
	11	35.2	8° 30′	9.4	1.33					15.72
	12	65	8° 45′	9.55	1.38					16.19
Catchment 3	13	75.2	5° 20′	6.1	1.07	0.28	654	0.1	0.68–0.82	16.06
	14	55.2	7° 30′	8.3	1.39					20.87
	15	62	7° 00′	7.7	1.33					19.97
	16	90.5	6° 40′	7.4	1.42					17.68
	17	58.1	8° 10′	9.07	1.63					24.47
	18	55	7° 30′	8.3	1.35					18.34

catchment 1), (2) 7.86–19.71 kg m^{-2} $year^{-1}$ (gully catchment 2) and (3) 16.06–-24.47 kg m^{-2} $year^{-1}$ (gully catchment 3). It is obtained from database that A_P of hillslope yields maximum erosion value due to high LS-factor (>1.50). It is found that if the slope is recognized as short length and high steepness, it has high potential for erosion (at dam sites 1, 2, 6, 11 and 14). Based on 18 dam sites, the average A_P is 16.63 kg m^{-2} $year^{-1}$ which is beyond the soil tolerance T-value limit (1.0 kg m^{-2} $year^{-1}$), showing high risk of erosion.

Analysis of RMMF Results

The climatic input parameters, i.e. mean annual rainfall 2016–2017 (R), number of rainy day (R_n) and mean rainfall (R_O), are based on the meteorological records of permanent stations. The effective rainfall (ER) (i.e. the remaining part of rainfall is stored and added in soil after leaf drainage and it has main role in water erosion) of the sample sites varies from 936 to 1057 mm, having leaf drainage (LD) of 88.34–290.16 mm and direct throughfall (DT) of 645.84–961.87 mm (Table 7.12). The parameters of topographic conditions (viz. slope angle, slope length and width) and soil–plant factors (i.e. soil surface roughness, canopy cover, ground cover, soil depth and plant height, etc.) are measured at field. Soil moisture content (MS), bulk density (BD), effective hydrological depth (EHD), soil erodibility index (K) and soil cohesion (COH) are measured by guide values of RMMF model (Morgan, 2001; Morgan & Duzant, 2008). The soil moisture at field capacity (R_c, % w/w) varies from

Table 7.12 Primary input parameters for RMMF model

Input data RMMF	ER	CC	LD	DT	R_c	GC	C
Catchment 1	936	0.13	121.68	814.32	9.96	0.12–0.44	0.41–0.78
		0.27	252.72	683.28	7.67		
		0.11	102.96	833.04	7.54		
		0.17	159.12	776.88	8.78		
		0.31	290.16	645.84	9.91		
		0.15	140.4	795.6	10.62		
Catchment 2	981	0.11	107.96	873.53	13.44	0.1–0.66	0.55–0.79
		0.09	88.34	893.16	12.67		
		0.14	137.41	844.09	14.72		
		0.15	147.22	834.27	11.64		
		0.09	88.34	893.16	15.9		
		0.17	166.85	814.64	14.48		
Catchment 3	1057	0.17	179.69	877.31	11.46	0.11–0.68	0.59–0.79
		0.11	116.27	940.73	10.72		
		0.15	158.55	898.45	10.25		
		0.12	126.84	930.16	12.67		
		0.09	95.13	961.87	11.55		
		0.19	200.83	856.17	10.72		

Table 7.13 Secondary input parameters for RMMF model

Input database RMMF	MS	E_t/E_o	EHD	BD	K	COH
Catchment 1	0.28	0.05–0.23	0.11–0.19	1.2	0.7	2
Catchment 2	0.28	0.25–0.32	0.08–0.12	1.2	0.7	2
Catchment 3	0.31	0.22–0.38	0.08–0.15	1.3	0.8	3

0.28 to 0.31 and other parameter is estimated as (1) actual to potential evapotranspiration (E_t/E_o, 0.05–0.38), bulk density (1.2–1.3 Mg m^{-3}), soil erobility index (0.7–0.8), ground cover proportion (0.1–0.68), canopy cover proportion (0.41–0.79) and crop cover proportion (0.09–0.31) (Table 7.13).

Based on the above estimates of inputs, firstly we have estimated the potential detachment rate of soil particle by raindrop (F) which does not vary to great extent in the catchments, i.e. 14.73–17.24 kg m^{-2}. Then, potential detachment by runoff (H) is estimated in 18 sites, and it varies from 0.88 to 5.07 kg m^{-2}, and the runoff amount (Q) fluctuates from 721.63 to 973.08 mm. The addition of F and H gives the total water erosion rate of catchments (as sediment phase of RMMF model). So, the total detachment rate (J) varies from 16.67 to 21.28 kg m^{-2}. The J values is compared with the potential transport capacity by runoff (G) which are very high in this region and G varies from 30.29 to 84.21 kg m^{-2} in 18 dam sites. In this case, J value is much less than *G* value (i.e. transport capacity is much higher than the sediment supply rate), so the erosion process is transport limited (here J < G, J value recognizes annual soil erosion rate). Ultimately, the predicted value of annual soil erosion rate (S_P) varies from 16.67 to 21.28 kg m^{-2} year^{-1} which exceeds the soil tolerance T-value limit of laterites (1.0 kg m^{-2} year^{-1}), showing high risk of erosion (Table 7.14).

Model Sensitivity Analysis

To measure the sensitivity of RUSLE, the maximum, minimum and average input parameters of rainfall (P), slope-length (LS), soil erodibility index (K) and crop cover (C) are used to estimate maximum, minimum and average output values of SE_P. On the slope element of gullies, all these input and output parameters are performed within the frame of RSULE (Table 7.15). The prime objective of sensitivity analysis is to measure the effects of variable input parameters on the output soil loss rate and to calculate the degree of sensitivity. Firstly, Average Linear Sensitivity (ALS) of P (R-factor) on the estimation of potential soil loss (SE_P) is 0.879. Then, ALS of LS-factor, K-factor and C-factor are 1.001, 0.999 and 1.001, respectively. So, it can be said that the LS-factor and C-factor (>1.0) are more sensitive in RSULE model to produce high deviation in SE_P values. K-factor is also highly sensitive, but the R-factor is not sensitive in RUSLE model. Therefore, to apply this model, we have to caution in measuring accurate slope angle, slope length, soil textural data and land use data.

Table 7.14 Summary of results and predicted erosion rates in RMMF model

Gully catchments	Check dam	Slope degree	Sin *S*	Runoff (mm)	Total KE Rainfall J m^{-2}	F kg m^{-2} $year^{-1}$	H kg m^{-2} $year^{-1}$	J kg m^{-2} $year^{-1}$	G kg m^{-2} $year^{-1}$	S_P kg m^{-2} $year^{-1}$ (mean = 18.63 kg m^{-2} $year^{-1}$)
Catchment 1	1	10° 09′	0.176	845.09	20,836	16.67	3.71	20.38	84.21	20.38
	2	11° 06′	0.192	965.74	18,950	15.16	5.07	20.23	78.79	20.23
	3	8° 30′	0.147	973.08	21,106	16.88	2.98	19.87	80.73	19.86
	4	6° 11′	0.107	905.25	20,298	17.24	1.63	18.87	35.95	18.87
	5	5° 50′	0.101	847.55	18,412	14.73	2.04	16.77	56.59	16.77
	6	8° 05′	0.14	813.21	20,567	16.45	2.56	19.01	60.18	19.01
Catchment 2	7	4° 30′	0.069	821.78	22,102	15.47	1.2	16.67	30.29	16.67
	8	5° 30′	0.088	854.99	22,383	15.66	1.98	17.64	45.67	17.64
	9	7° 20′	0.125	756.07	21,682	15.17	0.88	16.05	52.97	16.05
	10	3° 45′	0.057	905.77	21,542	15.08	0.93	16.01	36.94	16.01
	11	8° 30′	0.142	845.58	22,382	15.66	3.03	18.69	55.84	18.69
	12	8° 45′	0.139	829.96	21,262	14.88	2.82	17.7	55.53	17.7
Catchment 3	13	5° 20′	0.092	774.35	22,936	16.05	2.76	18.81	38.61	18.81
	14	7° 30′	0.13	808.23	23,844	16.69	4.59	21.28	60.29	21.28
	15	7° 00′	0.121	830.38	23,239	16.26	1.68	17.94	55.9	17.94
	16	6° 40′	0.116	721.63	23,692	16.58	2.28	18.86	47.72	18.86
	17	8° 10′	0.142	770.31	24,146	16.9	4.49	21.39	49.71	21.39
	18	7° 30′	0.133	808.48	22,633	15.84	4.44	20.28	53.89	20.28

Table 7.15 Average linear sensitivity analysis of RUSLE and RMMF

Input parameter	Maximum	Average	Minimum	ALS
RUSLE				
Rainfall (P)	1697	1523	1350	0.871
Slope-length factor (LS)	1.53	1.345	1.16	1.001
K-factor	0.31	0.25	0.19	0.999
C-factor	0.93	0.88	0.83	1.001
RMMF				
Rainfall (R)	1697	1523	1350	0.79
Slope steepness (S)	1106	832	558	1.001
K-factor	0.8	0.55	0.3	1.001
GC-factor	0.17	0.12	0.07	0.027

To measure the sensitivity of RMMF the maximum, minimum and average input parameters of rainfall (P), slope steepness (S), soil detachability index (K) and ground cover (GC) are used to estimate maximum, minimum and average output values of J. All the sensitivity analyses are done on the sample slope element of S1 (Table 7.15). The prime objective of sensitivity analysis is to measure the effects of sensible input parameters on the predicted values of soil loss, i.e. J, and to calculate the degree of sensitivity. It is found that the mentioned factors of S and CC are highly sensitive to erosion prediction accurately, because the both ALS value of K and CC is 1.001 which is greater than 1.0, i.e. highly sensitive index. The R-factor is moderately sensitive, as it values about 0.79, but GC factor is less sensitive. This analysis reflects that during the application and prediction of RMMF model, we should care about these input parameters.

Model Evaluation and Validation

In this part of model evaluation and validation, we have applied firstly absolute error, root mean square (RMS) error estimation, Chi-square test, model efficiency coefficient (MEC) and lastly scatter plot and linear regression ($Y_c = a + bx$), t-test of b value and product moment correlation (r) and coefficient of effectiveness (E_C) at 0.05 level of significance. The total statistical analysis is based on the measured erosion rate (O) and predicated erosion rate (A_P and S_P) with 18 sample size ($n = 18$).

Error Analysis

The absolute error between observed and predicted data is measured, showing positive anomaly (over estimation of erosion in response to observed rate) and negative anomaly (under estimation of erosion in response to observed rate) (Table 7.16). It is learned that 55.55% of predicated sample (i.e. ten dam sites)

Table 7.16 Summary of data error estimation, model validation and evaluation

O kg m^{-2} year^{-1} [m = 16.27]	A kg m^{-2} year^{-1} (m = 16.63)	S kg m^{-2} year^{-1} (m = 18.63)	(O-A)	RMS-error	MEC	E_c at 95% Con. Int.	(O-S)	RMS-error	MEC	E_c at 95% Con. Int.
14.1	15.89	20.38	−1.79	3.22	0.48	0.61	−6.28	4.45	0.22	0.38
19.94	16.74	20.23	3.2				−0.29			
24.27	18.7	19.86	5.57				4.41			
14.45	13.22	18.87	1.23				−3.42			
10.5	13.07	16.77	−2.57				−6.27			
24.01	20.87	19.01	3.14				5			
8.12	7.86	16.67	0.26				−8.55			
15.81	15.37	17.64	0.44				−1.83			
15.23	19.71	16.05	−4.48				−0.82			
10.15	8.44	16.01	1.71				−5.86			
20.82	15.72	18.69	5.1				2.13			
14.71	16.19	17.7	−1.48				−2.99			
15.05	16.06	18.81	−1.01				−3.76			
16.12	20.87	21.28	−4.75				−5.16			
19.24	19.97	17.94	−0.73				1.3			
11.87	17.68	18.86	−5.81				−6.99			
20.62	24.47	21.39	−3.85				−0.77			
17.97	18.34	20.28	−0.57				−2.31			

provide under estimation of erosion phenomena and 44.45% of data gives over estimation of erosion phenomena in RUSLE modelling. The value of absolute error varies from −5.81 to +5.57 from the observed data, and the estimated RMS-error is assigned as 3.22. In RMMF modelling, it is found that 77.17% of data sample (i.e. 14 dam sites) shows under estimation of erosion phenomena and 22.23% of data sample shows over estimation of erosion phenomena in respect to observed erosion rate. The absolute error value varies form −8.55 to +5.0 from the observed data, and the estimated RMS-error is assigned as 4.45. Therefore, it can be said that the RUSLE model gives less error than RMMF model.

Chi-Square (χ^2) Test Statistic

At 0.05 level of significance and 17 ($n-1$) degree of freedom, the Chi-square (χ^2) test statistic sets forth the null hypothesis (H_0, $O - A_P$ or $S_P = 0$) which states that there is no difference between certain characteristics of a population, i.e. difference between predicted and observed value is zero and good correlation. The alternate hypothesis (H_1, $O - A_P$ or $S_P \neq 0$) reflects significant difference between predicted and observed value. The value of χ^2 statistic is assigned as 27.59 at 0.05 significance level with 17 degree of freedom (Table 7.17). The χ^2 statistic values of RUSLE and RMMF modelling are estimated, respectively, as 10.43 and 20.10 which are much lower than the tabulated χ^2 value at 0.05 level. Therefore, it is concluded that H_0 is accepted and H_1 is rejected. So, there is no significant difference between observed and predicted values in the study. Another statistic p-value of this test is used to

Table 7.17 Results of testing statistics

Statistical parameter	Tabulated testing statistical value	Calculated value		Remarks on hypothesis
		RUSLE	RMMF	
Chi-square (χ^2)	χ^2 statistic is assigned as 27.59 at 0.05 significance level with 17 degree of freedom	10.43	20.10	H_0 is accepted and H_1 is rejected (both models are accepted and predicted values resemblance with measured values)
t-test statistic of r value	t statistic is assigned as 2.120 at 0.05 significance level with 16 degree of freedom	5.44	3.37	H_0 is rejected and H_1 is accepted (both models are accepted and there is god correlation)
t-test statistic of b value	t statistic is assigned as 2.120 at 0.05 significance level with 16 degree of freedom	2.99	1.71	H_0 is rejected and H_1 is accepted (regression value of RUSLE give desired result than RMMF)
Confidence interval, $\alpha_{0.05}$	14.15 to 18.29 kg m^{-2} year^{-1} at 0.05 significance level	61% of sample fallen within interval	38% of sample fallen within interval	RUSLE model can provide more satisfactory results than RMMF

know the quantitative level of acceptance and large p-value means weakness of alternative hypothesis. The estimated p-value of RUSLE modelling is 0.8844 which reflects that H_0 is accepted, having 88.44% chance of getting desired results, but in case of RMMF modelling, there is only 26.90% chance (p-value –0.2690) of getting desired results at 0.05 significance level. Now, it can be said that according to χ^2 test statistic, RUSLE model gives significant good results than RMMF model in this analysis.

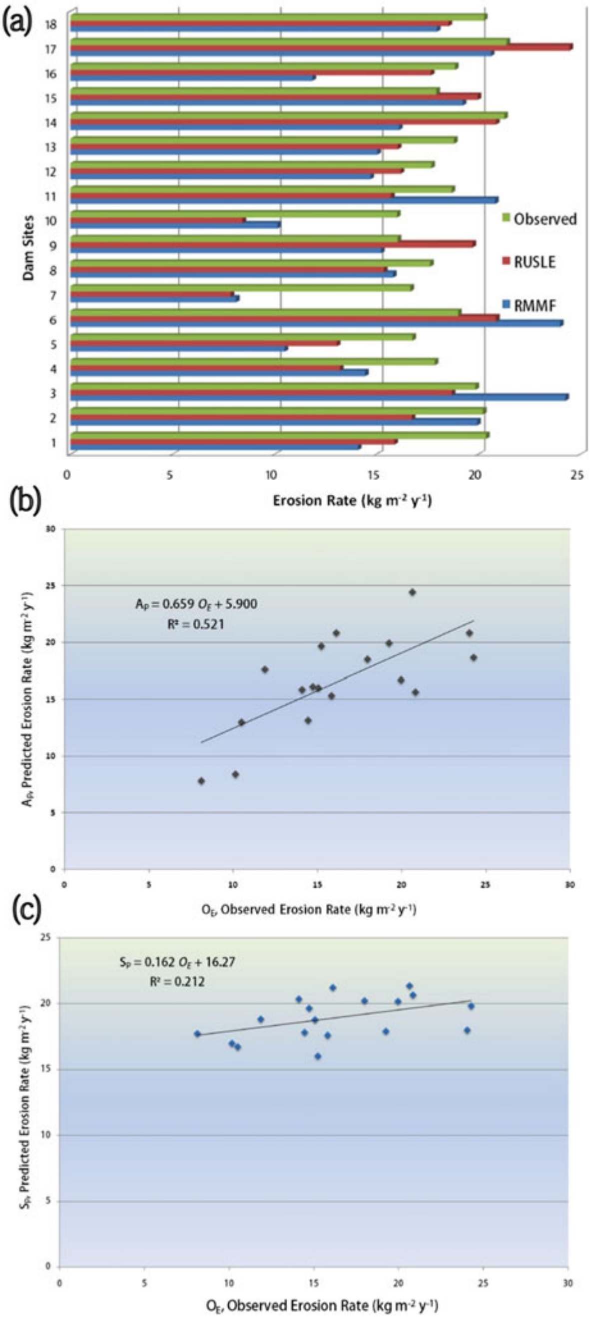
Model Efficiency Coefficient

Now, applying model efficiency coefficient (MEC) (Nash & Sutcliffe, 1970; Morgan & Duzant, 2008) into the relation between observed and predicted data, we have found two MEC values for two erosion models: (1) 0.48 (RUSLE) and (2) 0.22 (RMMF), respectively. The MEC >0.50–0.70 signifies good and satisfactory performance of model in reference to observed erosion results (Quinton, 1997; Morgan, 2011). The result shows that MEC value of RMMF is much lower than 0.50, but MEC value of RUSLE is much closer to 0.50. So, it can be decided that RUSLE model can be applied in this geo-climatic setting in place of RMMF model.

Linear Regression and *t*-Test Statistics

To get the trend of inter-relation between observed and predicted database, now the scatter plot and linear regression trend line ($Y_c = a + bX$) are prepared, taking observed data as X and predicted data of RUSLE and RMMF models as Y. It is finally estimated that the predicted values of RUSLE is statistically interrelated with the observed values ($A_P = 5.90 + 0.659\ O_E$), having good coefficient of determination (R^2) of 0.521 (i.e. inter-relation explained 52.10% in population) and notable slope (b) value of trend line, i.e. 0.659 (Fig. 7.9). The b-value of regression line (i.e. slope) reflects the quantitative judgment (indicating a change on response variable caused by a unit change of respective explanatory variable) of Y dependence on X. The t-test statistic of b value is 2.120 at 0.05 significance level with 16 ($n - 2$) degree of freedom (H_0: $b = 0$, Y does not depend on X; $H_1 - Y$ depends on X). The estimated values of t-test statistic are 2.99 (RUSLE) and 1.71 (RMMF). This analysis reflects that test statistic of RUSLE b-value is greater than the tabulated t-value, and it means high dependence of predicted values on the observed values (i.e. RUSLE predicted values resemblance with observed erosion rates). In other case, another analysis reflects that test statistic of RMMF b-value is lower than the tabulated t-value, and it means low dependence of predicted values on the observed values (i.e. RMMF predicted values do not resemblance with the observed erosion rates). The Pearson's product moment correlation (r) of this analysis is estimated as 0.72 for RUSLE and 0.56 for MMF which reflect good

Fig. 7.9 Comparing the final results between observed and predicted erosion rates—(**a**) composite bar diagram showing dam site-wise result deviations in observed (O_E) and predicted erosion rates (RUSLE and RMMF), (**b**) predicted erosion rate (A_P) of RUSLE has close resemblance with O_E, having 52.1% of explanation in relationship and (**c**) predicted erosion rate (S_P) of RMMF has very weak resemblance with O_E, having only 21.2% of explanation in relationship



correlation between predicted and observed values. Here, again the *t*-test statistic of *r* value is 2.120 at 0.05 significance level with 16 ($n - 2$) degree of freedom (H_0: $b = 0$, Y does not correlate with X; H_1—there is a good correlation between Y and X). The estimated values of *t*-test statistics are, respectively, 5.44 (RUSLE) and 3.37 (RMMF) which are much greater than the tabulated *t*-value at 0.05 significance level. Here, it can be concluded that *r* value or correlation between observed and predicted value is statistically significant in this study, but the results of RUSLE modelling correlate highly with the observed erosion rates than RMMF modelling.

Effectiveness Coefficient

At last, the effectiveness coefficient (E_C) of erosion model is applied on the basis of linear regression database, 0.05 confidence interval of observed erosion rate (O_E) and Z-value of 1.96. The calculated R_{diff} value (relative difference) varies from +0.196 to −0.139 in RUSLE and + 0.34 to −0.09 in RMMF, respectively. It is found from the regression analysis ($R_{diff} = m \log_{10} O_E + b$) that 55.55% of RUSLE results is placed in over-predicted zone, whereas 77.7% results of RMMF is located in over-predicted zone (Fig. 7.10). It generally reflects, from the logarithmic relation between R_{diff} and O_E, that RMMF model generates an over-predicted result of the reality, i.e. always providing high erosion rate than observed rate. The confidence interval of observed erosion rate is 14.15–18.39 kg m^{-2} year^{-1}. If the large number of predicted values is fallen within this confidence interval, then E_C yields high value, signifying the good performance of the model. In general, E_C is the ratio between number of sample fallen within confidence interval and total number of sample. E_C of RUSLE modelling is 0.61 and the value is 0.38 in case of RMMF modelling. Therefore, it can be concluded that at 0.05 significance of confidence interval RUSLE model can provide satisfactory results in this region.

7.5 Discussion

Erosion Intensity

In spite of above quantitative analysis, one key question is always raised by soil scientists, agriculturists and land developers is that 'how serious is erosion in this study area'? The first part of the answer to this question involves establishing typical value of soil erosion by measured data and models: (1) field measured data −8.12 to 24.01 kg m^{-2} year^{-1} (mean 16.27 kg m^{-2} year^{-1}), (2) RUSLE data −7.86 to 24.47 kg m^{-2} year^{-1} (mean 16.68 kg m^{-2} year^{-1}) and (3) RMMF data −16.01 to 21.28 kg m^{-2} year^{-1} (mean 18.63 kg m^{-2} year^{-1}). It is needed to compare the research results with the T-value to understand the critical level of erosion which can be reduced to an acceptable limit using crop management and land management techniques. Erosion is natural geological process, and it is impossible to stop; instead

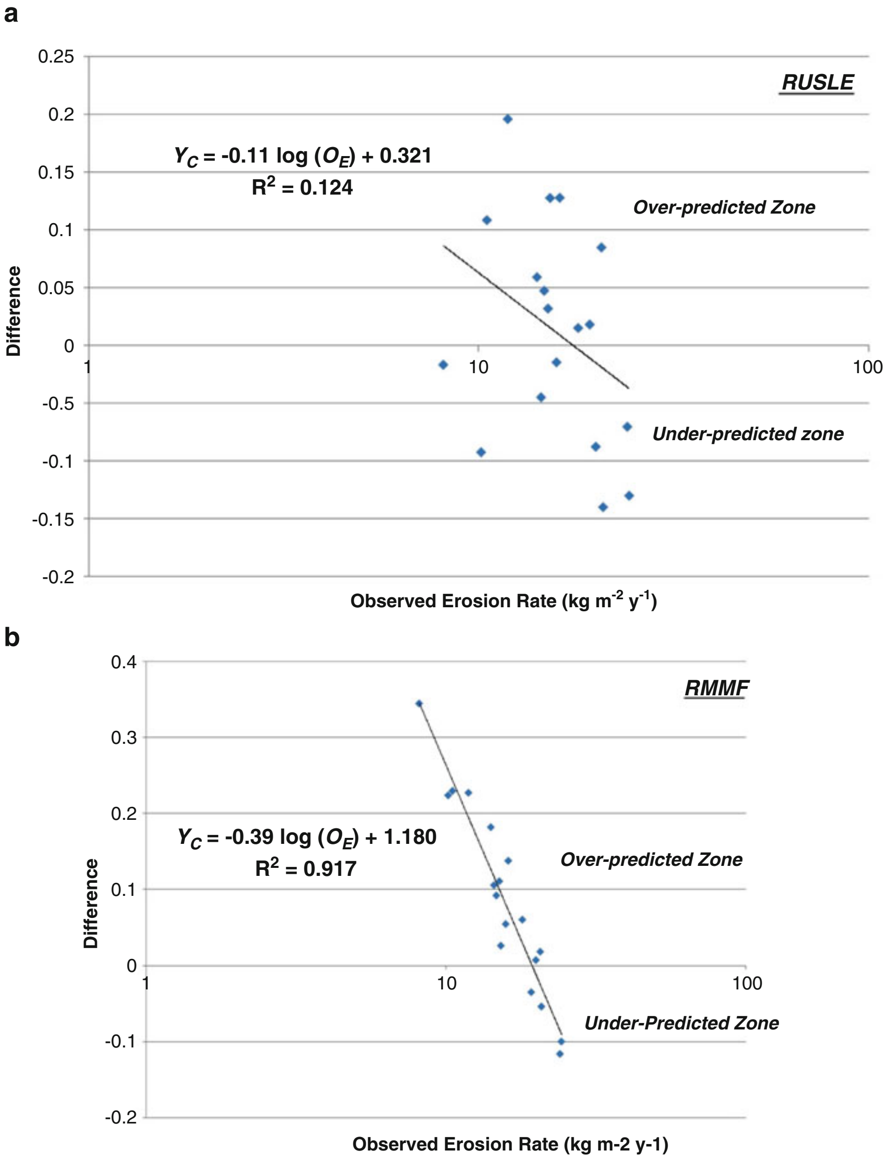


Fig. 7.10 Logarithmic relationship between relative differences of results (R_{diff}) and observed erosion rate: (**a**) high variations of R_{diff} (RUSLE) in relation to logarithmic increase of O_E, and (**b**) low variations of R_{diff} (RMMF) in relation to logarithmic increase of O_{E} and high numbers of over-predicted results

the goal is to manage environmental and human impacts on the soils so that the rate of erosion is within an acceptable range. It is found that T-value of 1 kg m^{-2} year^{-1} (i.e. 10 t ha^{-1} year^{-1}) is experimentally proved in the red and lateritic soils of West Bengal (Mandal & Sharda, 2013; Lenka et al., 2014). The T-value signifies the permissible limit to a level of crop and biomass productivity to be sustained economically in the study area.

The observed and predicted erosion rates show very higher value than the T-value, reflecting rugged—dissected terrain, low productivity of crops and high expansion of badlands. The results of erosion rate justify the escalating vertical erosion of gullies (i.e. up to 1.5–3.5 m depth) which unearths the underlying pallid kaolinte zone and occasionally weathered bedrock. Now, unit of mass per area per time can be converted into equivalent depth of soil thickness which is eroded permanently. Montgomery (2007) used a standard bulk density of 1200 kg m^{-3} in the paper to get the loss of soil thickness per year (i.e. dividing the annual erosion rate by bulk density of eroded materials). Applying the bulk density of eroded materials (i.e. 1.717 kg m^{-3} in study area) and observed erosion rates, it is found that soil thickness of 0.47–1.41 cm year^{-1} (mean 0.95 cm year^{-1}) is permanently lost from the lateritic surface of the catchments. In addition Montgomery (2007) developed an empirical equation to estimate the average time period (T_c, in years) taken to erode that soil thickness, viz. $T_c = S/E - P$ (where S is initial thickness or depth of soil profile, E is rate of soil thickness loss and P is the average soil production rate, 0.2 mm year^{-1}). Using this equation to this study, it is learnt that the water erosion will require 127–223 years (average 176 years) to erode the mean soil thickness of 1500 mm in this region.

Factors of Erosion

The observed erosion rates and predicted erosion rates show that the mean annual erosion rates vary from 16.27 to 18.63 kg m^{-2} year^{-1}. The high value of erosion rate reflects the ultimate development of dense network of gullies in the laterite terrain. In the saturation condition of peak monsoon and cyclonic rainfall period, the surface crusting (i.e. Fe-Al clay closes the pore spaces of top soils) and less canopy cover on bare soil promotes high overland flow on the slope elements. Here, the gully erosion signifies instability in the landscape, and it is regarded as a threshold condition under certain topographic parameters in the landscape, relating with overland flow erosivity and surface resistance of laterite terrain (Ghosh & Guchhait, 2020). High runoff, due to intense rainfall, is the primary trigger, but the local conditions such as slope morphometry (i.e. high concavity at the base of slope), land use (i.e. high proportion of bare soil cover and low proportion of canopy cover) and soil characteristics (high erodibility and surface crusting) control the triggering of gully erosion (Ghosh & Guchhait, 2020). It is found that 52.51% of gullies are affected by overland flow erosion (slope steepness, S, 1.2–5.2° and drainage area, A, 2129.1–10513.9 m^2), while 27.96% belongs to landslide erosion (S 5.2–9.5° and A 457.1–5702.5 m^2)

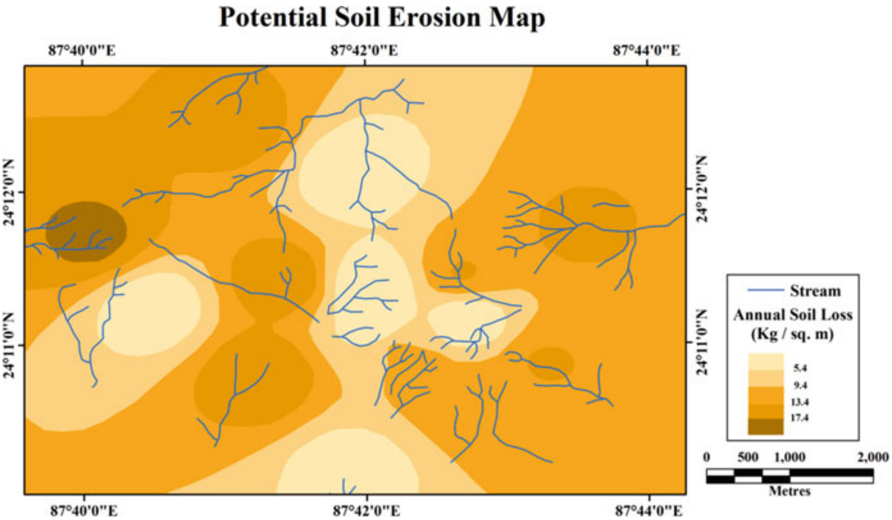


Fig. 7.11 RUSLE erosion map depicting (rill and inter-rill erosion) spatial coverage of different zones of annual soil erosion rate (kg m^{-2} year^{-1}), considering 17 catchments of gullies

(Ghosh & Guchhait, 2020). This experimental study and model evaluation is suggested that instead of using RMMF model, the RUSLE model can be applied for this lateritic region to estimate potential rate of annual soil loss. Therefore, based on the 17 sub-catchments of gullies (a part of study area) and RUSLE modelling (considering 118 gully head slope), an erosion map is developed to depict the potential annual rate of soil loss due to rill and inter-rill erosion in the lateritic region. The erosion map (Fig. 7.11) shows that the western and eastern part is very much susceptible to soil erosion (greater than 9.4 kg m^{-2} year^{-1}) due to high LS factor and bare soil cover, but the erosion rate (less than 9.4 kg m^{-2} year^{-1}) is much lower in the central part, because this part is covered with Acacia plantation, Sal forest, aerodrome pavement and relatively low LS factor. Also it is understood that the whole region is under very high erosion risk, because the erosion rate is beyond the acceptable T value limit (i.e. 1 kg m^{-2} year^{-1}).

The most vulnerable sites of water erosion (need to be protected) are identified as (Ghosh et al., 2020): (1) the region above the gully heads where the rills have tendency to converge; (2) high steepness (>5°) and long stretch of convex slope (>70 m); (3) the region having high bareness of slope and surface crusting promotes more runoff; and (4) bank failure due to mass wasting, pipe flow, flow convergence at heads and undercutting by channel flow. The fundamental problem to control soil erosion is centred on the on-site management of too much runoff water in short span of torrential rains or thunderstorms. To check channel erosion, the prime focus of erosion control strategies should be placed on five aspects: (1) reducing discharge rate through good growth of vegetation at catchment and water retention basins; (2) minimizing channel grade through construction of check dams and rock chutes for enhancing deposition; (3) controlling headcut erosion through drop structures at catchment to recue concentrated flow areas; (4) constructing flow barriers (as gravel or sand bags or loose rock piles) to control downstream sediment movement; and (5) promoting vegetative measures (plantation of trees and grasses on bare surface) to control splash, rill and gully erosion throughout the basin.

7.6 Conclusion

Now it can be said at last that the present research work has fulfilled the objectives with mentioning the region as a high potential erosion risk at basin scale using measured data and models (16.27–18.63 kg m^{-2} $year^{-1}$). Using limited database and resources, the research has successfully applied the erosion models and compared the results against field measured erosion data to get the real picture of laterite badlands. The experimental design and plan of work reaffirm that RUSLE model gives desire results in comparison to RMMF model with very high model efficiency coefficient (0.48) and effectiveness coefficient (0.61). The predicted values of RUSLE (A_P) follow the field measured data (O_E), with a positive correlation ($r = 0.72$) and trend line ($Y_c = 5.9 + 0.659\ O_E$) which is not very resemblance in case of RMMF model. It is learned from the analysis that the logarithmic relation, between R_{diff} (relative difference) and observed erosion rate (O_E), reflects more over-prediction of erosion results (i.e. yielding high predicted erosion rate than O_E) in case of RMMF modelling than RUSLE. The measured data of erosion rate confirms the vulnerability and high erosion risk of the region against T-value (1.0 kg m^{-2} $year^{-1}$) of laterite soils. It is found that the mean soil thickness of 0.95 cm per year is permanently lost from the surface of gully catchments. Applying RUSLE model in the whole study area, it is estimated that the region is dissected by annual erosion rates of 5.25–18.12 kg m^{-2} $year^{-1}$.

The most challenging task is to apply rightly an erosion model understanding the geo-environmental conditions which can be measured accurately through input variable functions of that model. The more inputs in field-based data collection, innovative techniques, flexibility of model application and better understanding of hydro-geomorphic processes will help to get good prediction in the soil erosion research. No model can give exact results in comparison to observed data at plot scale or basin scale, but high expertise and fine tuning of advanced model can provide sufficient inference on the erosion rates. It is understood that there is a need of further research to apply RUSLE or RMMF models in different parts of India for the applicability and validity of model. Validation of any erosion model can only be done or justified scientifically if the GIS-based model data will evaluate with the observed data taken at field plots. At last, the present study reveals that anyone cannot blindly exercise any erosion model and prepare any thematic map of soil erosion spatially in any particular region without evaluating the scale effect and error statistics of predicted values in comparison to field measured data.

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