

Estimation of soil Erosion and Risk Assessment using the RUSLE Model in Google Earth Engine (GEE): A Case Study of the Dulung River Basin, West Bengal, India

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ABSTRACT

Accelerating land degradation driven by water induced soil erosion pose one of the most critical threats to agriculture sustainability and watershed health humid subtropical region of India. This Study presents a spatially explicit assessment of soil erosion risk across the Dulung River Basin (116,385.72 ha) in Jhargram district, West Bengal, employing the Revised universal Soil Loss Equation (RUSLE) model integrated within the Google Earth Engine (GEE) cloud computing platform. Multi source geospatial dataset including CHIRPS 2023 precipitation recodes, NASA SRTM 30 m digital elevation data, Open Land Map, soil texture grids at 250 m resolution, Sentinel-2 multispectral imagery at 10 m resolution, and ESA World Cover 10 m land cover maps were used to compute the five RUSLE factor layers: rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), cover management (C), and support practice (P). Estimated Average annual soil loss across of the basin is 15.64 t ha⁻¹ yr⁻¹. The Spatial distribution reveals that 36.04% of the basin comes under the moderate erosion class (10-20 t ha⁻¹ yr⁻¹), while 39.68% records only slight loss (<10 t ha⁻¹ yr⁻¹). Zones of high, and severe erosion collectively affect 24.23% of the area, concentrated primarily in the steep terrain of the northern sub catchments. The LS factor emerged as the dominant driver of spatial variability in erosion intensity. Spatially, Severe to high erosion is concentrated in the northern Binpur-I and Binpur-II blocks, particularly around Shyam Sunderpur, Dharsa, Parihati, Kanimahuli, and Gidhni, where steep lateritic slopes and sparse vegetation amplify soil loss. The central Jamboni and Jhargram blocks fall within moderate to high erosion range, while the southern Gopiballavpore-II and Sankrail blocks record the lowest erosion rates owing to gentle terrain and dense agricultural cover. The findings provide a basin wise erosion risk inventory that can guide prioritisation of conservation interventions such as contour bunding, terracing, and vegetative buffers in the most vulnerable zones.

INTRODUCTION

Soil erosion by water remains a omni present and unsupervised from of land degradation globally. The detachment and redistribution of surface soil by rainfall impact and overflow strips of agricultural fields of their nutrient-rich topsoil layer, progressively, loading rivers and reservoirs with sediment (Wischmeier & Smith, 1978; Renard et al.,1997). Globally, estimates place soil losses from water erosion at tens of billions of tonnes annually, with consequences ranging from reduced crop yields and silted irrigation infrastructure to downstream flooding and water-quality impairment (Borrelli et al., 2017).

In India, there is intense soil erosion. Due convergence of high intensity



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monsoon rainfall, widespread agricultural expansion, deforestation for cultivation, overgrazing, and inadequate adoption of soil conservation practices, this country losses significant amount top soil every year (Pandey et al., 2007; Prasannakumar et al., 2012). The sub-humid and seasonally dry regions of eastern India including the lateritic uplands of West Bengal are especially vulnerable because shallow, structurally fragile soil sit atop dissected terrain that amplifies runoff energy during the kharif monsoon season (Narayan & Babu, 1983).

It is technically demanding expansive and logically impractical for directly field management of soil at watershed. Established empirical models that link measurable environmental factors to predicted soil loss therefore play a central role in erosion assessment. Among these, the Revised Universal Soil Loss Equation (RUSLE) has gained widespread adoption because it operates on six factor layers rainfall erosivity (R), Soil erodibility (K), slope length and steepness (LS), cover management (C), and support practice (P) that can each be derived from readily available geospatial datasets (Renard et al., 1997). Unlike process based alternatives such as WEPP or SWAT, RUSLE demands comparatively modest parameterisation and produces spatially distributed outputs when implemented in a GIS or remote sensing environment (Panagopoulos & Koutsoyiannis, 2018).

The emergence of Google Earth Engine (GEE) as a cloud based geospatial analysis platform has significantly lowered the computational barriers to applying RUSLE at regional scales (Gorelick et al., 2017). GEE provides direct access to satellite image archives, climate datasets, and terrain data at planetary scale, enabling researchers to compute multi layer RUSLE factor maps, perform raster algebra, and generate spatially explicit erosion risk maps without the need for local high performance computing infrastructure (Velasquez Montoya et al., 2023). Recent applications have demonstrated the capacity of GEE-RUSLE workflows to produce accurate basin scale erosion inventories across topographically diverse environments in Africa, the Middle East, and South Asia (Desale et al., 2023; Waseem et al., 2023).

The Dulung River Basin which is a fifth order left bank tributary of the Subarnarekha River, travel across the lateritic upland zone of Jhargram district, West Bengal. The basin is defined by a patchwork of forest, cropland, and settlement land covers distributed across a dissected terrain with pronounced slope gradients in the northern reaches. Despite its ecological and agricultural significance, no spatially unambiguous, quantitative assessment of soil erosion risk has previously

been published for this basin. This study addresses that gap by applying the RUSLE model in GEE, integrating high resolution multi source datasets to generate a spatially distributed annual soil loss map, identify erosion hotspots, and assess the relative contribution of each RUSLE factor to Overall erosion Intensity.

STUDY AREA

The Dulung River Basin covers approximately 116,385.72 ha and is situated primarily in Jhargram district of West Bengal (86.5%), with a smaller segment extending into Purba Singhum district of Jharkhand (13.5%) (Dandapat et al., 2020). The basin stretches across latitudes 22°09'N to 22°34'N and longitudes 86°39'E to 87°04'E (Dandapat et al., 2020). The Dulung River originates near Dulungdiha Mouza in the Binpur Block and eventually joins the Subarnarekha River near Rohini in West Bengal, having traversed a total channel length of approximately 110 km within Jhargram District (Dandapat et al., 2020; Sarkar & Patel, 2011). Three Principal headstreams Katchua Khal, Dakai Khal, and the Dulung itself feed the upper catchment, which is further drained by several named tributaries including Deb Nala, Kupan Nala, Gandharpi Nala, Shimana Nala, and Bansi Khal (Dandapat et al., 2020).

Physiographically, the northern and western portions of the basin consist of dissected lateritic uplands with slope gradients frequently exceeding 20%, whereas the central and southern zones grade into broader alluvial floodplains with gentler relief (Sarkar & Patel, 2011; Jana, 2022). average annual rainfall in the Basin is around 1,362.55 mm, concentrated throughout the June to September southwest monsoon period. This pronounced seasonal rainfall seasonality, combined with the erodible nature of lateritic soils and varying vegetation density across land-cover types, creates a heterogeneous erosion risk landscape (Dandapat et al., 2020; Pandey et al., 2007). Administrative blocks within the West Bengal portion include Sankrail, Gopiballavpore-II, Binpore-I, Binpore-II, Jamboni, and Jhargram (Fig. 1).

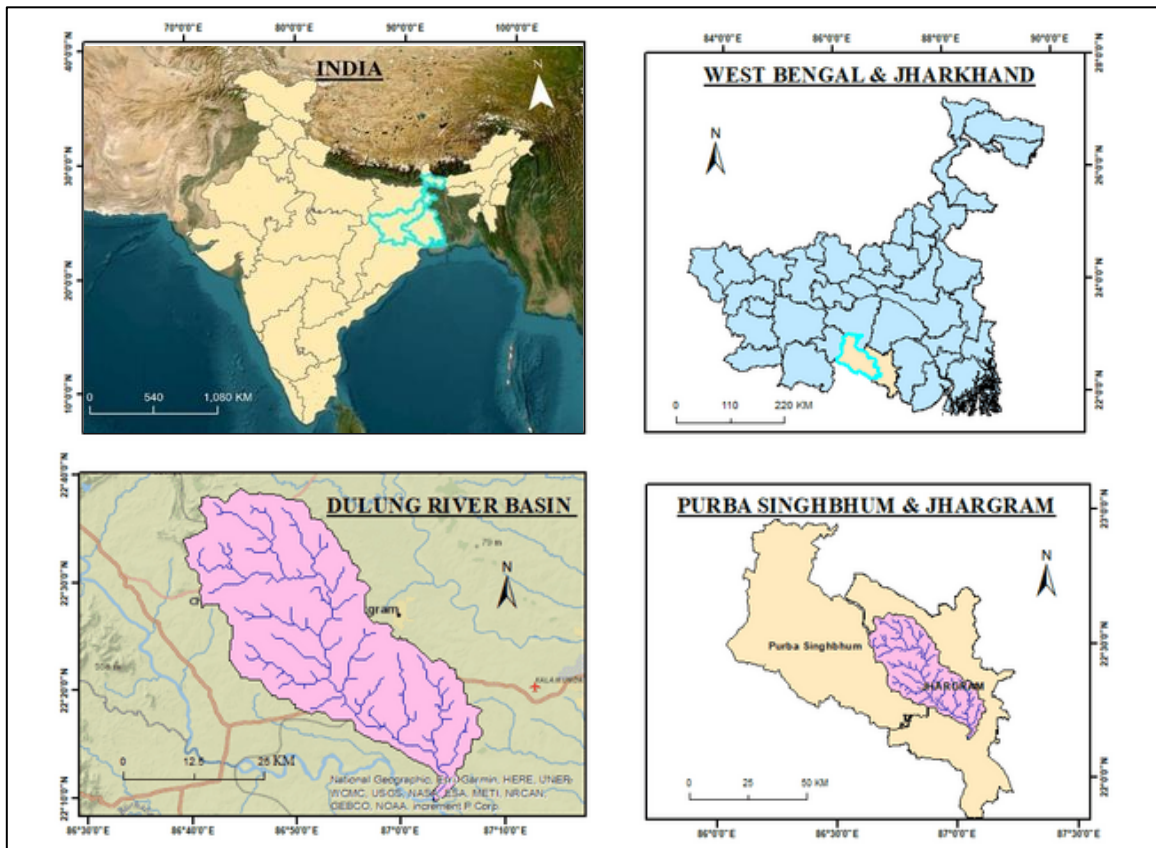


Fig .1: Study area Map of Dulung Basin

METHODOLOGY

Data sources

The study integrates five categories of geospatial datasets, all processed within the GEE environment. Table 1 Summarises the data types, providers, Spatial resolutions, Temporal coverages, and their specific roles in the RUSLE computation chain.

Table .1: Multi-Sources geospatial Datasets in the study

Data Type	Dataset	Source	Spatial Resolution	Time Period	Application
Digital Elevation Model	SRTM DEM	NASA/ USGS- GEE	30 m	2000	Slope, LS factor
Rainfall	CHIRPS Daily Precipitation	Climate Hazards Group, UCSB	5km	2023	R factor
Soil Texture	OpenLandMap Soil Texture	OpenLandMap/ ISRIC	250 m	2020	K factor
Satellite Imagery	Sentinal-2 Surface Reflectance	ESA/ Copernicus	10 m	2023	NDVI, C factor
Land Cover	ESA WorldCover200	European Space Agency	10 m	2023	LULC, P factor
Basin Boundary	Dulung Basin Shapefile	HydroSHEDS/ Derived			Study Boundary

Method

Soil loss was estimated using the multiplicative RUSLE equation (Equation 1):

$$A = R \times K \times LS \times C \times P$$

Where A is the computed average annual soil loss (t ha⁻¹ yr⁻¹); R is the rainfall erosivity factor (MJ mm ha⁻¹ h⁻¹ yr⁻¹); K

is the soil erodibility factor ($t\ ha\ h\ ha^{-1}\ MJ^{-1}\ mm^{-1}$); LS is three dimensionless slope length and steepness factor; The conceptual workflow from raw datasets through individual factor computation to the final erosion map is illustrated in. Fig.2. Each step was implemented as a GEE JavaScript script. A brief description of each factor follows.



Fig. 2: Methodological Flowchart

Google Earth Engine Platform

GEE is a cloud-based planetary-scale geospatial analysis environment developed by Google that provides free access to an extensive catalogue of satellite imagery and derived geospatial products, together with parallel processing infrastructure for raster computations (Gorelick et al., 2017). Its code editor accepts JavaScript based scripts that operate directly on server side data without the need to download or locally store large datasets. For this study, all RUSLE factor calculations, raster overlays, and spatial statistics were executed on the GEE platform, which allowed seamless

integration of datasets from different providers and at different native resolutions. All layers were rescaled to a common 30 m grid resolution and clipped to the Dulung River Boundary prior factor computation

Rainfall Erosivity Factor (R)

The R factor is using to quantify the capacity of rainfall to unfasten and transport soil particles. It is proportional to the total kinetic energy of rain events and the maximum 30 minute rainfall intensity (I30). For this study, monthly CHIRPS(Climat Hazard Group InfraRed Precipitation with Station data) precipitation data for 2023 were obtained through GEE and the R factor was computed following the empirical relationship of (Wischmeier and Smith, 1978) as modified for monthly data by (Arnoldus 1980) (Equation 2):

$$R = \sum [1.73 \times 10^{(1.5 \times \log(\frac{Pm^2}{Pa}) - 0.08188)}]$$

Where Pm is monthly rainfall (mm) and Paa is mean annual rainfall (mm). A spatially uniform distribution of R was estimated given the coarse native resolution (approximately 5.5 km) of CHIRPS data relative to basin extent. R values across the basin ranged form approximately rainfall regime.

Soil Erodibility Factor (K)

The K factor characterises the susceptibility of a given soil type to detachment and transport by rain splash and surface runoff, and it integrates the influence of soil organic carbon content , texture (sand , silt, and clay fractions), permeability, and structure (Mhaske et al.,2021). K value for this study were derived from the OpenLandMap soil texture classification (250 m resolution) accessed via GEE, using the look up formula of Williams et al. (modified by Shabani et al., 2014 (Equation 3):

$$K = \left(0.2 + 0.3e^{-0.0256.SAN.(1-\frac{SILL}{100})} \right) \cdot \left(\frac{SILL}{CLA + SIL} \right)^{0.3} \cdot \left(1 - \frac{0.25C}{C + e^{3.72-2.95C}} \right) \cdot \left(1 - \frac{0.75sn}{sn + e^{22.95n-5.51}} \right) \cdot 0.1317$$

Where SAN, SIL, and CLA represent the percentage mass fraction of sand, silt, and clay respectively; sn=1 SAN/100; and C denotes the mess Fraction of soil organic carbon (%). The dominant soil texture in the basin is Sandy Clay Loam (44.55%; K= 0.0394) and Loam (36.82%; K= 0.0423), with smaller areas of silty clay loam (18.46% ; K= 0.0499) and Sandy Clay (0.14% ; K= 0.045). resulting K values span 0.00 to 0.06 $t\ ha\ h\ ha^{-1}\ MJ^{-1}\ mm^{-1}$.

Slope Length and Steepness Factor (LS)

The LS factor is used to record the combined effect of hillslope length and gradient on the erosive power of overland flow. The slopes which are Longer and Steeper concentrate more runoff and produce greater kinetic energy to soil particles, thereby accelerating erosion rates (Montgomery, 2007). The SRTM 30 m DEM (Fig.3) obtained from GEE was used to drive slope angle (Fig.4) and flow accumulation (Fig.5) layer following the method of Desmet and (Govers., 1996). The LS value for each pixel was computed using (Equation 4):

$$LS = \left(\frac{\text{Flow Accumulation} \cdot \text{Cell Size}}{22.13} \right)^{0.4} \times \left(\frac{\sin(\text{Slope}) \cdot 0.01748}{0.09} \right)^{1.4}$$

The LS value across the basin from 0.00 to 90, indicating strong topographic heterogeneity. The northern highland sub catchments, which receive concentrated flow steep lateritic escarpments, generated the highest LS value and corresponding represent the topographically driven erosion hotspots of the basin.

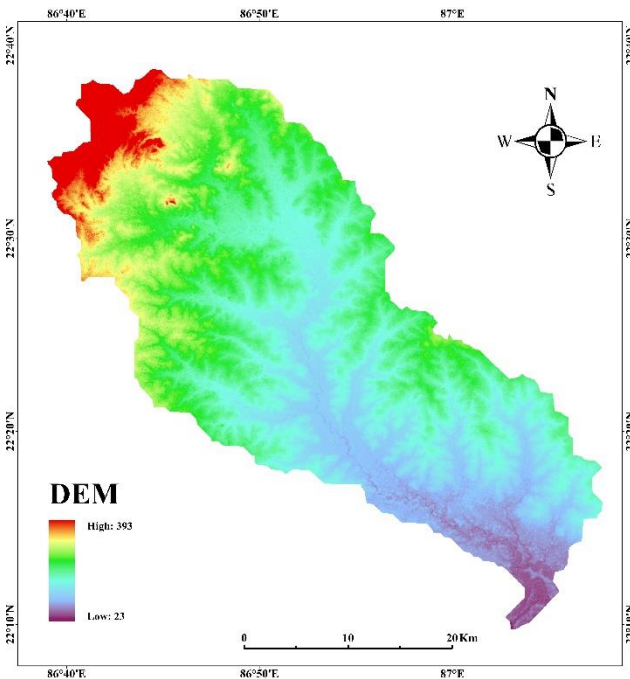


Fig. 3: Digital Elevation Model of Dulung River Basin

Cover Management Factor (C)

The C factor is used for showing the ratio of soil loss under a specific land cover and management combination relative to loss from a continuously tilled, bare-fallow reference condition. It ranges from 0 (complete surface protection) to 1

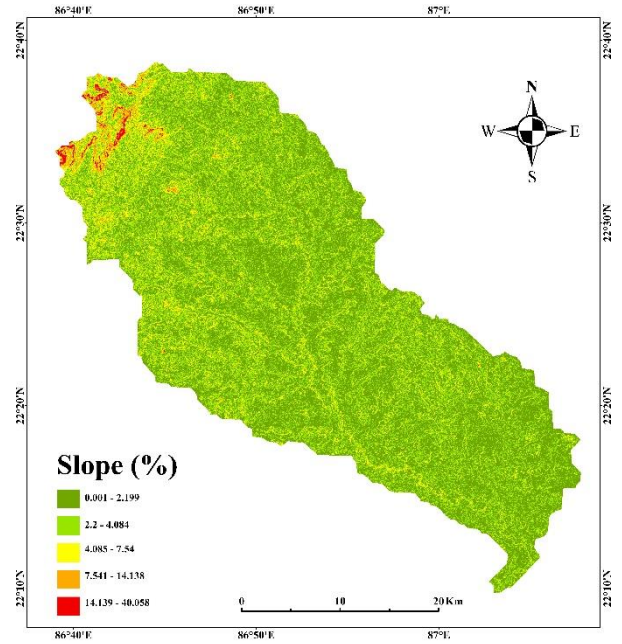


Fig. 4: Slope map of Dulung River Basin

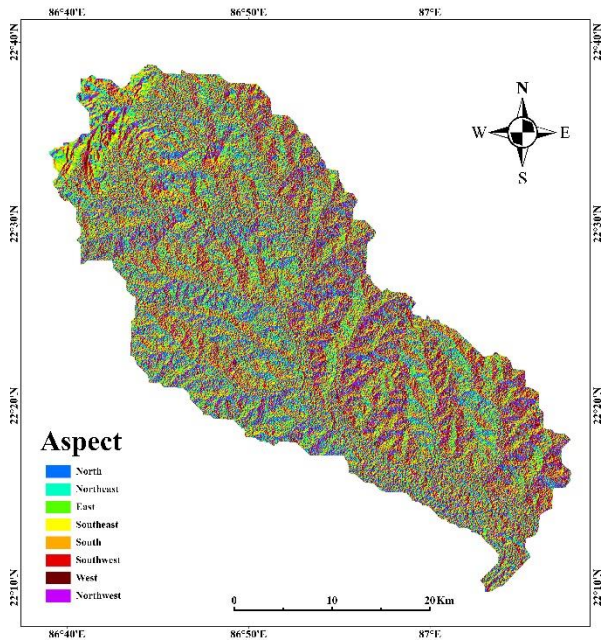


Fig. 5: Aspect map of the Dulung River Basin

(no vegetation cover). C was calculated from the Normalised difference Vegetation Index (NDVI) derived from cloud free sentinel-2 imagery acquired over the basin in 2023, following the exponential relationship of Van der Knijff et al., (Equation 5):

$$NDVI = \frac{NIR - R}{NIR + R}$$

$$C = e^{-\alpha \cdot \frac{NDVI}{\beta - NDVI}}$$

Sentinal-2 imagery was preprocessed to surface reflectance with atmospheric correction applied; all selected scenes had cloud cover below 5%. NDVI values across the basin ranged from 0.0 to 0.85. Dense forest patches returned NDVI values approaching 0.85, corresponding to C values near 0.001, while bare or sparsely vegetated land yielded C values approaching 1.0.

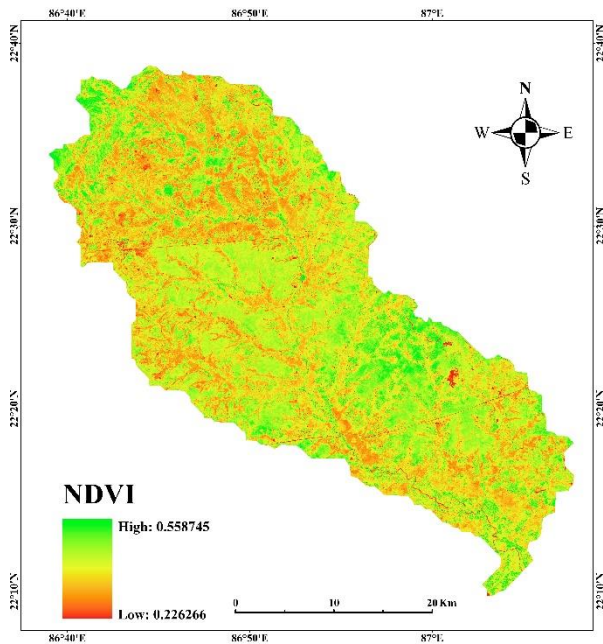


Fig .6: NDVI map of the Dulung River Basin

Supporting Practice Factor (P)

The P factor reflects the influence of specific erosion control practices such as contour ploughing, strip cropping, terracing, and subsurface drainage on reducing the rate of soil loss relative to upslope and downslope farming without such measurables (Renard et al., 19970). P varies from 0 (maximum conservation effectiveness) to 1 (no conservation measures). Because field level support practice data were unavailable for the study area, P was derived from the ESA WorldCover 10m landcover classification using a land use based assignment scheme: agricultural land was assigned $P=0.39$ and all other land cover categories were assigned $P=1.0$, following the approach of (Papaiordanidis et al., 2019). The approach is a standard simplification when field survey data on conservation practice adoption are absent.

RESULTS AND DISCUSSION

Results

Land Use and Land Cover Distribution

Land use and land cover classification based on ESA WorldCover 10m imagery recognised five major landcover categories within the Dulung River Basin (Table 2). Cropland constitutes the largest single land use type, accounting for 52.09% (60,590.03 ha) of the basin, reflecting the dominance

Table .2: LULC area statistics for the Dulung River basin

Land Cover Class	Land Use Category	Area (ha)	Area (%)
1	Vegetation	54,525.06	46.63
2	Cropland	60,590.03	52.09
3	Built-up	914.14	0.81
4	Water Bodies	186.33	0.16
5	Barren land	416.17	0.36

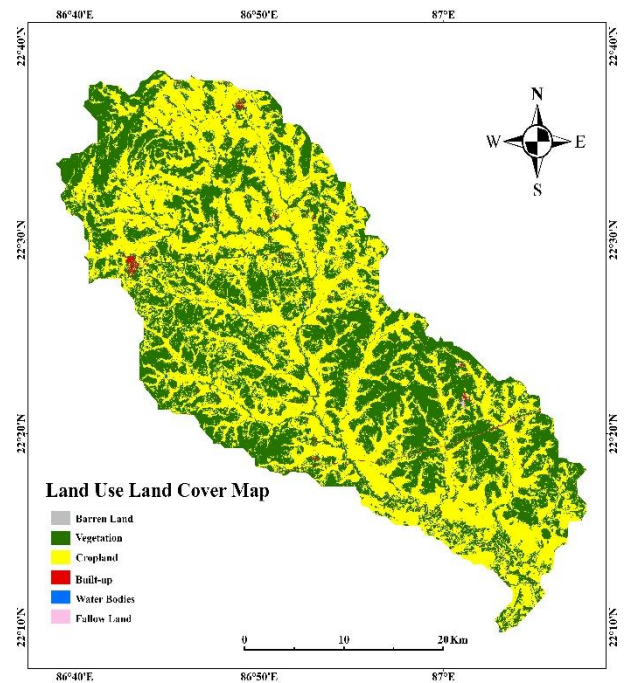


Fig .7: Land use land cover map of the Dulung River Basin

of paddy cultivation and seasonal agriculture in the flatter, lower-elevation portions of the basin. Vegetation (forest and mixed shrubland) ranks second at 46.63% (54,252.06 ha), concentrated in the northern upland and hill margin zones where canopy cover remains intact and provides substantial protection against erosion. Built-up areas, water bodies, and Barren land together account for the remaining 1.33% of basin area. The preponderance of cropland and vegetation translates into a C factor spatial pattern dominated by moderate to low erosion risk across most of the basin, with higher risk cells occurring where barren patches and sparse shrubland overlie steep slopes (Fig.7)

Rainfall Erosivity Factor (R)

Rainfall erosivity values computed from 2023 CHIRPS monthly precipitation data ranged from approximately 300 to 900 MJ mm ha⁻¹ h⁻¹ yr⁻¹ across the basin (fig. 8). The spatial pattern broadly follows the distribution of annual rainfall, with higher R values in the northern sub-catchments that receive more orographically enhanced precipitation than the southern lowland zones. The mean annual rainfall of approximately 1362.55 mm implies a substantial energy input from the monsoon season, which in combination with the relatively short and intense rainfall events characteristic of the pre monsoon and active monsoon phase, results in erosion events of high kinetic energy. Elevated R values correspond directly to areas with higher modelled annual soil loss, confirming that temporal and spatial variability in rainfall is a primary driver of erosion intensity across the basin (kinnell, 2010).

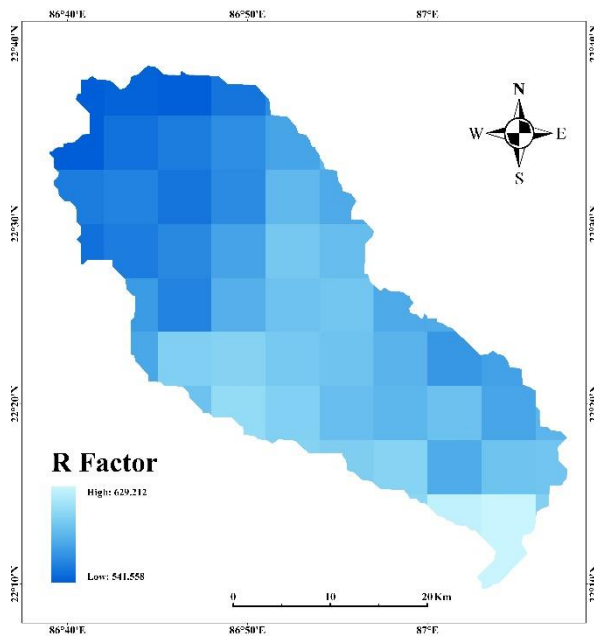


Fig. 8: R factor map

Soil Erodibility Factor (K)

The K factor map generated from the OpenLandMap soil texture data revealed values ranging from 0.0 to 0.06 t ha h MJ⁻¹ across the Dulung Basin (Fig. 9). Sandy Clay Loam, which dominates 44.55% of the basin, holds a K value of 0.0394, indicating moderate susceptibility to particle detachment. Loam soils (36.82% of basin) carry a slightly higher erodibility coefficient of 0.0423. Silty Clay Loam the most erodible class present is distributed across 18.46% of the basin with K=0.0499. The comparatively low proportion of sandy Clay (0.14%) limits the influence of this class on basin

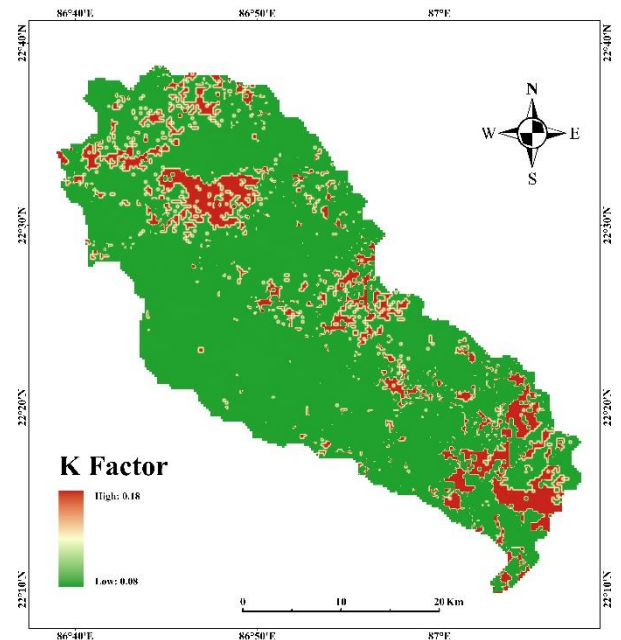


Fig. 9: K factor map

and central part of the basin correspond to areas where Silty Clay Loam and Sandy Clay Loam texture coincide with sparse vegetation, compounding erodibility with reduced cover protection.

Slope length and steepness factor (LS)

The LS factor exhibits the widest dynamic range of all five RUSLE inputs, Spanning 0.0 to 90 across the basin (Fig. 10). This reflects the pronounced topographic contrast between

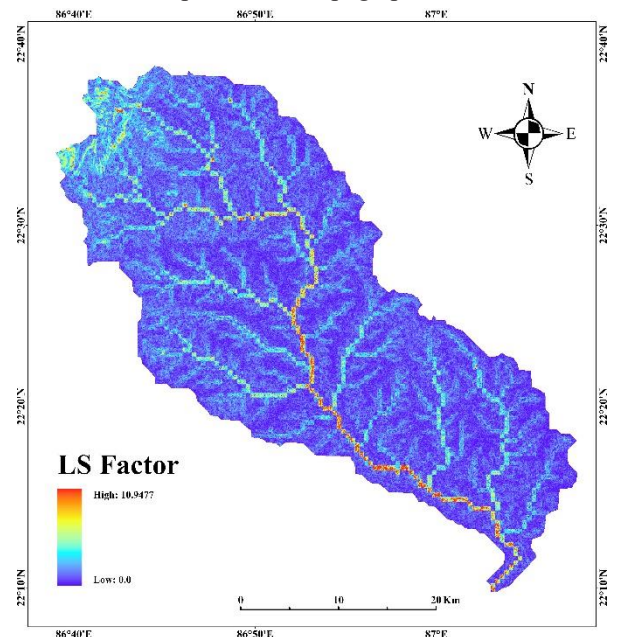


Fig. 10: LS factor map

the steeply dissected lateritic uplands of the northern reaches and the near flat alluvial plain in the south. LS value exceeding 20 are confined to the northern hilly corridor, where flow accumulation on long, steep slopes generates the most erosive flow conditions. Gentle slope in the agricultural floodplain zone yield LS values well below 5, substantially dampening erosion potential despite similar rainfall input. As the dominant multiplicative driver in the RUSLE computation, the LS factor ultimately controls the spatial pattern of high soil loss cell: the northern sub catchments, characterised by LS values of 20-90, account for the majority of very high and severe erosion areas identified in the final soil loss map (Wischmeier & Smith, 1978; Montgomery, 2007).

Cover Management Factor (C)

C factor values across the basin ranged from near zero in densely forested hill zones to approximately 1.0 in bare land patches (Fig.11). Forest areas, which hold NDVI values between 0.6 and 0.85, produced C values of approximately 0.001, confirming the strong protective effect of intact canopy and litter layer against raindrop impact and sheet erosion. Cropland returned NDVI values in the 0.2-0.5 range during the growing season, corresponding to moderate C values, while barren and sparsely vegetated areas yielded C values approaching 1.0, making them highly susceptible even on relatively gentle slopes. The spatial coincidence of high C values with moderate to steep LS terrain is the primary explanation for the erosion hotspot clusters observed in the final soil loss map.

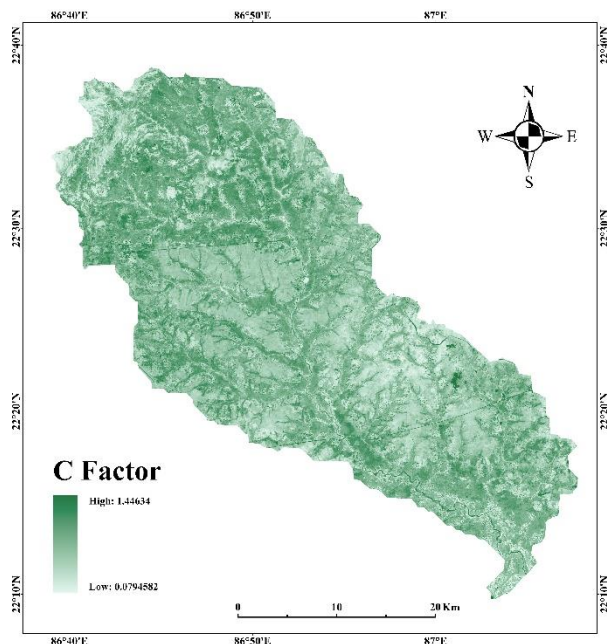


Fig .11: C factor map

Support practice Factor (P)

In the absence of field data on conservation practice adoption, the P factor was assigned based on land use classification: cropland areas received $P=0.39$, acknowledging the partial reduction in erosion achieved by prevailing cultivation practices such as field bunding and seasonal tillage management, while non-agricultural floodplain and mid slope terrace zones, and uniform values of 1.0 across forested and barren areas. This approach provides a conservative estimate of conservation effectiveness and is consistent with comparable RUSLE studies conducted in the absence of plot level support practices or practice records (Papadouranidis et al., 2019).

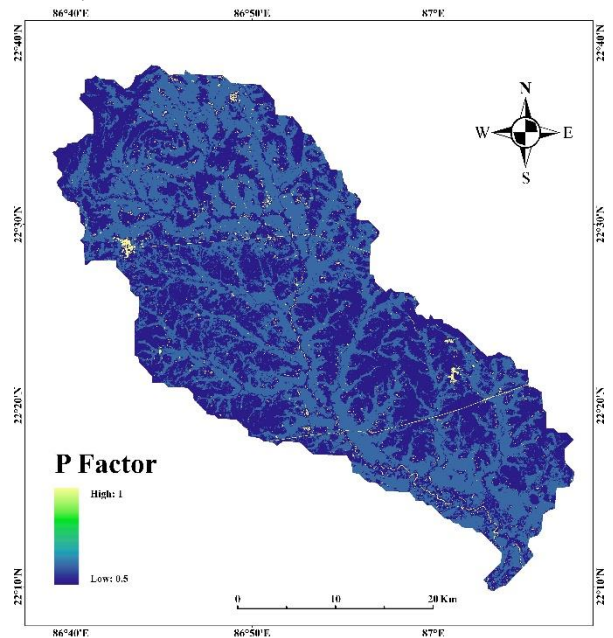


Fig .12: P factor map of the Dulung Basin

Soil Loss Estimation and Spatially distributed annual soil loss map for Dulung River Basin

(Fig. 13). The mean estimated soil loss is $15.64 \text{ t ha}^{-1} \text{ yr}^{-1}$. Table 3 presents the areal breakdown by severity class.

The largest share of the basin 39.68 % falls within the slight erosion class ($<10 \text{ t ha}^{-1} \text{ yr}^{-1}$), corresponding predominantly to densely forested hill slopes and floodplain zones where low C and LS values combine to constrain erosion. The moderate class ($10\text{-}20 \text{ t ha}^{-1} \text{ yr}^{-1}$), covers 36.04% of the basin, mainly the transitional slope positions and mixed cropland vegetation zones of the mid basin. Together, these two classes account for 75.72% of total basin area, showing that a large proportion of the landscape does not fall under immediate severe erosion stress.

The remaining 24.23% of the basin, however, experiences high to sever erosion. High erosion (20-30 t ha⁻¹ yr⁻¹) affects 14.19% of the area, while very high (30-40 tha⁻¹ yr⁻¹) and severe (>40 t ha⁻¹ yr⁻¹) classes account for 5.14 % and 4.90% respectively. These high loss cells cluster tightly in the northern sub catchments where elevated LS values(exceeding 20) coincide with moderate to high erodibility soils and relatively sparse vegetation. Through they

Table .3: Annual soil loss classification table

Class	Severity Category	Soil Loss (t ha ⁻¹ yr ⁻¹)	Area (ha)	Area(%)
1	Slight	<10	46,204.53	39.68
2	Moderate	10-20	41,967.41	36.04
3	High	20-30	16,521.03	14.19
4	Very High	30-40	5985.11	5.14
5	Severe	>40	57708.08	4.90
Total		Mean: 15.64	116386.16	

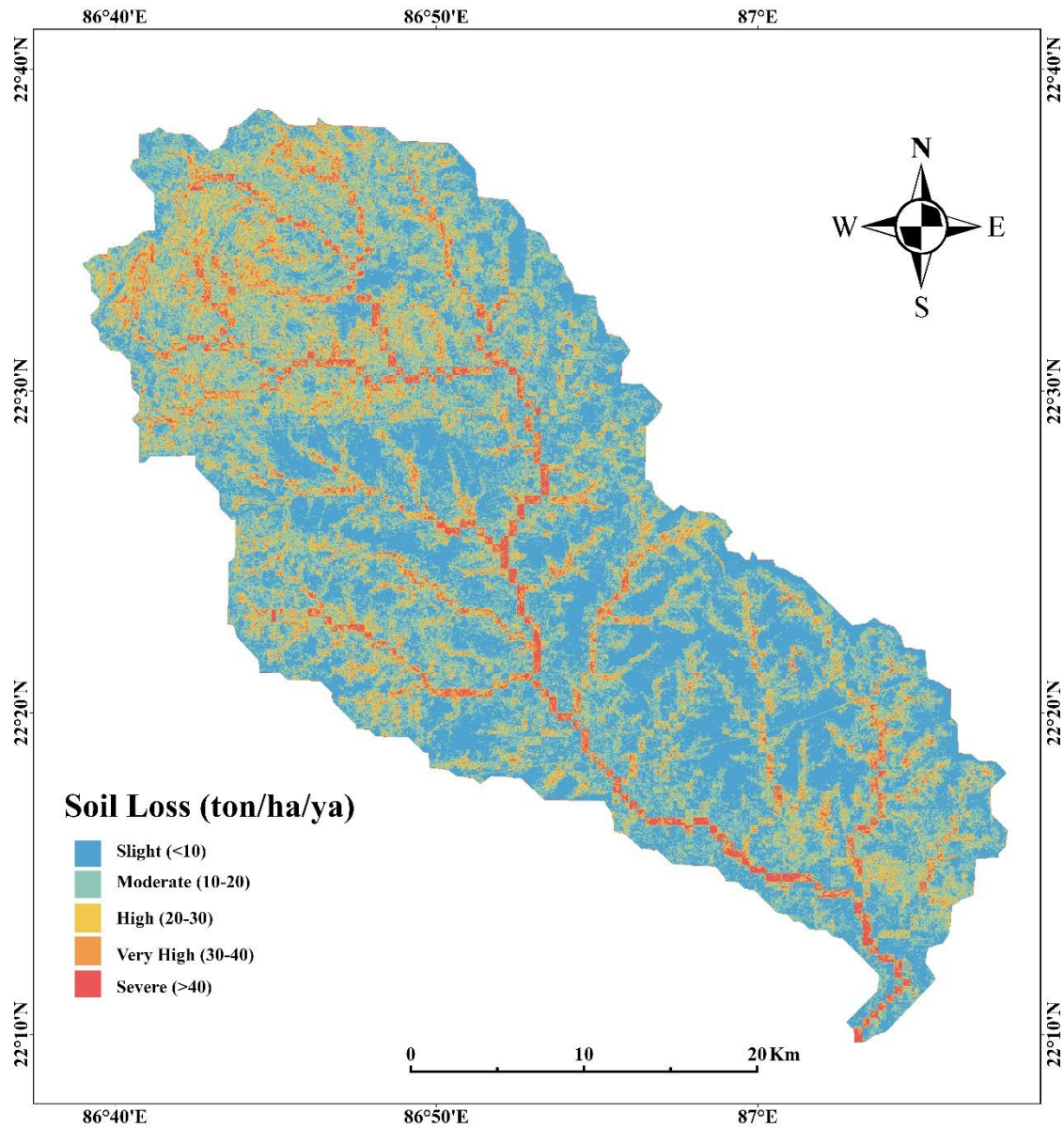


Fig .13: Study area Map of Dulung Basin Annual soil loss map for Dulung River Basin

Discussion

The estimated mean soil loss of 15.64 t ha⁻¹ yr⁻¹ for the Dulung River aligns with values reported from comparable watershed studies in the sub humid lateritic uplands of eastern India and other seasonally wet tropical catchments. The spatial pattern of erosion risk is strongly shaped by the interaction between the LS factor which captures the amplifying role of terrain in concentrating runoff and the C factor, which modulates the degree to which vegetation intercepts rainfall energy before it reaches the soil surface. This interplay means that the same rainfall erosivity input produces dramatically different soil loss rates depending on local slope geometry and vegetation density, a finding consistent with the broader RUSLE literature (Renard et al., 1997; Montgomery, 2007).

The dominance of the LS factor as the primary spatial driver of erosion risk has direct implications for conservation planning. Because slope geometry cannot be altered except through expensive civil engineering works (terracing, check dams), the most cost effective management lever available to land managers is the C factor specifically, increasing vegetation density on steep, currently sparse cover hillslope through afforestation and controlled grazing programmes. Additionally, the targeted application of conservation practices (P factor reduction) on agricultural slope through contour bunding and graded bunds could meaningfully reduce erosion from the substantial proportion of the basin under cropland.

The Spatial distribution of erosion risk across the Dulung River Basin shows a clear north to south gradient that aligns closely with the physiographic structure of the catchment. The northern sub catchments, corresponding to the Binpur-I and Binpur-II administrative blocks, represent the critically affected zone. Localities such as shyam Sunderpur, Dharsa, Perihati, Kanimahuli, and Gidhni are situated on steeply dissected lateritic uplands where slope gradients frequently exceed 20%, generating LS values in the range of 20 to 90. In these areas, very high and severe erosion class (>30 t ha⁻¹ yr⁻¹) dominate, driven by the combined effect of high and silty Clay Loam soil, and Comparatively sparse or degraded vegetation cover that yields elevated C factor values. The headwater sub-catchments fed by Katchua Khal, Dakai Khal, and upper Dulung Channel, along with tributary nalas such as Deb Nala, Kupan Nala, and Gandharpi Nala, further concentrate overland flow energy in these localities, amplifying detachment and transport rates beyond what slope steepness alone would predict.

The central zone of the basin, encompassing the Jamboni

block adjoining areas including Bairgram, Jamboni Market, and localities extending toward Jangal Khas in the east, falls predominantly within the high to moderate erosion range (10-30 t ha⁻¹ yr⁻¹). This mid-basin zone is characterised by transitional slope positions where the lateritic uplands grade into broader valley floors. The patchwork of cropland and residual forest cover here produces an intermediate C factor, while LS values, though lower than in the north, remain high enough to sustain moderate C factor locally high runoff erosivity. The Jhargram block, situated in the eastern margin of the basin, shares a similar erosion character, with moderate loss rates over mixed agricultural and built-up surfaces and slightly higher rates on the steeper interfluvies that separate the Dulung drainage from adjacent catchments to the east. These central and eastern localities are where the interaction between agricultural land use and residual slope gradient is most evident, and where targeted counter bunding and vegetative buffer strip along field margins would yield the most measurable reduction in erosion with the least disruption to ongoing cultivation.

The southern part of the basin, covering the Gopiballavpore-II and Sankril administrative blocks, records the lowest erosion class (<10 t ha⁻¹ yr⁻¹). Localities such as Sardiha, Chandri, Chichra, Belaberya, and Gopiballabpur town lie on broad alluvial floodplains and low gradient valley floors where LS values remain well below 5. Although rainfall erosivity in this southern zone is broadly similar to the rest of the basin, the near flat to gently rolling terrain removes the topographic amplification that drives severe erosion in the north. Dominant paddy cultivation and riparian vegetation along the Subarnarekha corridor further suppress erosion through relatively high C factor protection during the active cropping season. Within the Sankrail block, the eastern fringe localities adjacent to the basin margin record marginally higher loss rates where the terrain shows a slight re-steepening, but these remain within the moderate erosion class. Collectively, the north to south gradient in erosion severity reinforces the importance of topographic control as the overriding determinant of spatial risk distribution within the Dulung River Basin, and provides a clear geographic framework for spatially targeting conservation investments: immediate priority should be given to the northern Binpur blocks, with secondary priority to the central Jamboni-Jhargram zone, and maintenance monitoring for the relatively stable southern floodplain areas.

Several limitations of this study merit acknowledgment. First, the R factor was derived from CHIRPS data at approximately 5.5 km native resolution, which may fail to capture sub grid

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spatial variability in rainfall intensity important for sub watershed scale patterns. Scaled, the P factor assignment relied entirely on land use class rather than actual field survey of conservation practice adoption, potentially overestimating erosion on cropland where farmers have independently installed field bunds or practice conservation tillage. Third, RUSLE as an empirical model does not account for sediment delivery processes that is, not all detached soil reaches the model to estimate sediment yield at the basin outlet, enabling comparison with measured suspended sediment loads.

CONCLUSION

This study presents the first spatially explicit, quantitative assessment of water induced annual soil erosion across the Dulung River Basin (116,385.72 ha), West Bengal, using the RUSLE model implemented in Google Earth Engine.

The mean annual soil loss across the basin is estimated at 15.64 t ha⁻¹ yr⁻¹, with the majority of the basin area (75.72%) falling within the slight to moderate erosion classes. Approximately 24.23% of the basin faces high to severe annual soil loss (>20 t ha⁻¹ yr⁻¹), accumulated in the steep northern sub catchments. Spatially, severe to very high erosion is concentrated in the northern Binpur-I and Binpur-II blocks, particularly around Shyam Sunderpur, Dharsa, Parihati, Kanimahuli, and Gidhni, where steep lateritic slope and vegetation amplify soil loss. The central zone across the jamboni and jahrgam blocks, including Bahirgram and jangal Khas, falls within the moderate to high erosion range under mixed cropland and transitional slopes. The southern floodplain blocks of Gopiballavpore-II and Sankrail, covering localities such as Sardiha, Chandri, Chichra, and Belaberya, record the lowest erosion rates owing to gentle terrain and dense agricultural cover. The LS factor, reflecting the long and steep slopes of the northern lateritic uplands, is the primary driver of spatial variability in erosion intensity. The P and C factor play a secondary but important modulating role; agricultural land, despite lower slope gradients, contributes disproportionately to basin wide erosion because of its large areal extent and moderate C values. The GEE based RUSLE workflow proved effective for integrating multi resolution, multisource dataset into a coherent, basin scale erosion risk map, and can be readily replicated or updated as new satellite data become available. The erosion risk zonation produced by this study provides a prioritisation framework for conservation investments: afforestation on steep barren slopes, promotion of contour bunding on agricultural terraces, and installation of check dams in high LS gully heads represent the highest impact interventions for reducing soil and sediment loss from Vol. 1, No. 2, 2026 • **Geospatial and Earth System Science**

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Data Availability Statement

Whatever dataset used in this study are publicly available and where access through the Google Earth Engine. DEM data from USGS GEE, Rainfall data from Climate Hazard group (CHIRPS), Soil data from OpenLandMap, satellite image from European Space Agency Sentinel-2, and LULC data from ESA WorldCover. These data are openly available.

The processed data are available from the Corresponding author upon reasonable request.

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