Soil erosion estimation using USLE/RUSLE in Kaski district

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Abstract

Soil erosion is a major environmental concern in Nepal's mid-hill regions, particularly in areas like Kaski District where steep slopes, intense rainfall, and changing land use contribute to land degradation. This study aims to assess soil erosion loss in Kaski District by applying the Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss Equation (RUSLE) models. Utilizing available datasets such as SRTM DEM for slope and aspects data, CHIRPS rainfall data, NARC soil data and ICIMOD land use landcover map, soil erosion loss maps were generated to identify soil erosion patterns. The results show that both USLE and RUSLE models effectively captured the spatial variability of soil erosion across the district, with USLE producing slightly higher estimates than RUSLE. Erosion rates were found to be lower in the southern parts of the district and increased progressively toward the northern mountainous regions. The model outputs were consistent with findings from previous studies in Kaski and similar terrain, supporting the validity of these models for erosion prediction in Kaski. The study highlights the usefulness of USLE and RUSLE as practical tools for soil loss estimation and provides a foundation for future research, land management planning, and soil conservation initiatives in the region.

Keywords: *Soil Erosion, RUSLE, USLE, Kaski*

1. Introduction

Soil erosion, defined as the removal of topsoil through the combined action of water, wind, and inappropriate human activities(Lal, 2001), represents one of the most pressing environmental challenges of our time. Globally, this process affects approximately 75 billion tons of soil annually (Borrelli et al., 2017)with Lal (2001)emphasizing that such rates exceed natural soil formation processes by 10 to 100 times in vulnerable regions. The consequences are particularly severe in developing nations like Nepal, where steep terrain, intense monsoon rainfall, and unsustainable agricultural practices create a perfect storm for topsoil loss (Chalise et al., 2019).

In Nepal, soil erosion is especially severe in the Middle Hills region, where terraced farming and deforestation have accelerated land degradation. Studies indicate that soil loss rates in some parts of the country exceed 40 tons per hectare annually, far above the tolerable limit of 10-12 tons per hectare (Bajracharya & Sherchan, 2009) The Kaski district, located in the Gandaki Province, is no exception. Its varied landscape, ranging from the low-lying Pokhara Valley to the steep slopes of the Annapurna range, makes it highly susceptible to erosion. Rapid urbanization, expansion of agricultural land, and deforestation for fuel and timber further exacerbate the problem (Ghimire et al., 2013) Without proper intervention, continued soil erosion in Kaski could lead to irreversible environmental damage, threatening local livelihoods and ecosystem services.

Among various soil erosion prediction approaches, the Universal Soil Loss Equation (USLE) and its enhanced version, the Revised Universal Soil Loss Equation (RUSLE), have proven particularly effective for mountainous regions like Kaski. The original USLE (Wischmeier & Smith, 1978) provides a simple yet robust framework using only five factors (R, K, LS, C, P), making it adaptable even in data-scarce regions. RUSLE (Renard et al., 1994) builds upon the framework with several key improvements: (1) enhanced rainfall erosivity (R) calculations better suited for monsoon climates, (2) updated soil erodibility (K) values for diverse soil types, and (3) improved slope length/steepness (LS) computations for complex terrain. While more sophisticated models like WEPP (process-based) or SWAT (watershed-scale) exist, RUSLE offers distinct advantages :lower data requirements than process-based models, proven reliability in Himalayan conditions(Bhattarai & Dutta, 2007), and seamless integration with GIS for spatial analysis (Panagos et al., 2015). This combination of simplicity and accuracy makes RUSLE and USLE particularly valuable for local-scale conservation planning in Nepal's Middle Hills. Use of RUSLE was done to estimate the soil erosion in Nepal where remote sensing data and local meteorological data(Koirala et al., 2019) and in other parts of Nepal such as Dolkha (Thapa, 2020) and mainly in Kathmandu district(Dahal, 2020) as well as in Bagmati basin(Gelal et al., 2024). RUSLE for soil loss estimation Himalayan regions(P. Joshi et al., 2023). Use of USLE in soil loss estimation was conducted in Nepal at 2001 A.D (Gardner & Gerrard, 2001) and in upper region of Kathmandu district(Dangol & Mandal, 2023). The reviewed literature confirms that the Revised Universal Soil Loss Equation (RUSLE) has become the dominant soil erosion model in Nepal, largely superseding the original USLE due to its enhanced capacity to incorporate dynamic factors like seasonal vegetation cover (C-factor) and improved slope-length calculations (LS-factor)(Renard et al., 1994) . While both models rely on similar core principles, RUSLE's adoption is evident in >80% of post-2010 studies based on Google Scholar analysis. Use of Global datasets such as SRTM, Soilgrids, etc. has make the RUSLE more favorable than other soil loss models. Despite the use of RUSLE and USLE, there seems to be lack of use of local and updated dataset in the soil estimation studies. Most studies, especially which use RUSLE model use global outdated dataset such as Soil grids, digital soil data form FAO. There is only small initiative to use local data in some studies. Research on soil estimation in the region is scarce, with only a handful of studies available, including those conducted in the Gandaki Basin (Subedi et al., 2017), Phewa Lake, Kaski (Bista & Basnet, 2017).Here, there seems to be lack of latest soil erosion loss map which is essential to understand the soil loss pattern as well as to employ soil conservation ma required places.

The main objective of this study is to assess soil erosion risk in Kaski District using the RUSLE and USLE models to generate a soil erosion loss map. Our research incorporates updated land cover data, localized rainfall records, and local soil data to improve prediction accuracy. The results will not only identify critical erosion hotspots but also evaluate recent soil erosion patterns based on the available datasets. By providing a soil erosion model and map, the study aims to enhance stakeholders' understanding and support further research, such as soil loss prediction and prevention studies.

2. Materials and Methods

2.1 Study Area

Nepal is a mountainous country, categorized into three major ecological regions: the Mountain, Hill, and Terai. Administratively, it is divided into seven provinces and 77 districts. Among these, Kaski District is located in Gandaki Province. Geographically, it lies in the southern part of the Annapurna mountain range, encompassing portions of the Annapurna massif and the city of Pokhara. The district is situated in the central region of the country, spanning latitudes 28°12' N to 28°36' N and longitudes 83°40' E to 84°12' E. Kaski covers an area of approximately 2,017 square kilometers, accounting for 1.41% of Nepal's total land area.

Kaski District, nestled in Nepal's Gandaki Province, exhibits a complex and dynamic geology, characterized by dramatic variations in topography, landforms, and erosion susceptibility. The region spans three major ecological zones: the high Himalayan mountains in the north (part of the Annapurna range), mid-hills with steep slopes and valleys, and lower river basins such as the Pokhara Valley. The northern sector consists of rugged, snow-capped peaks exceeding 8,000 meters, with bare, fractured rock faces and glacial moraines, which contribute to high erosion potential.

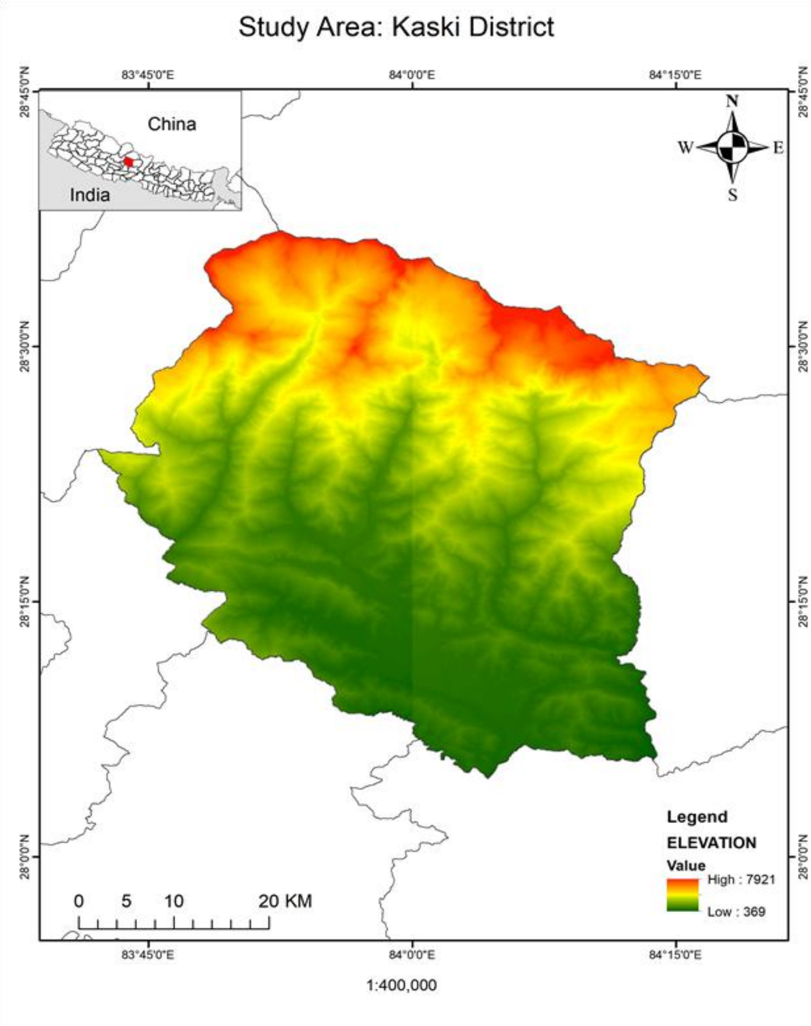

Fig. 32: Study Area Location

2.2 Dataset and software used

2.1.1 Dataset

Table 5: Input dataset

Dataset	Resolution	Source	Year of Acquisition(A.D.)
Sentinel-2 image	10m	Copernicus hub	2022
NASA SRTM DEM dataset v003	30m	From USGS website	2014
Climate Hazards Center Infrared Precipitation with Station data (CHIRPS)	250m	CHIRPS website	2022
Soil data	100m	NARC in collaboration with CIMMYT	2022
Landuse Landcover (LULC) map	30M	ICIMOD	2022

2.1.2 Software used

Table 6: Software used

Software	Remarks
Google Earth engine	Access and processing of dataset
Arc Map of ArcGIS	Calculation and visualization of data and result

2.3 Methodology

2.3.1 Workflow

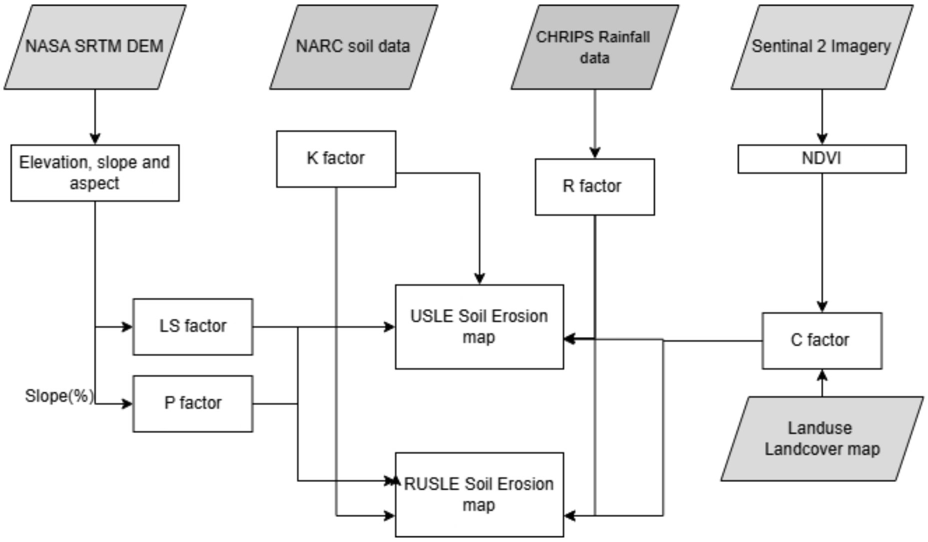

Fig. 33: Workflow of the study

2.4 RUSLE and USLE model

The Universal Soil Loss Equation (USLE) was developed by Wischmeier and Smith (1965, 1978) to predict annual soil loss from sheet and rill erosion on agricultural land. The Revised USLE (RUSLE) (Renard et al., 1994)improved upon Wischmeier and Smith's original model with updated erosion factor calculations and expanded applicability to different land uses. Formula for RUSLE and USLE are both same with five factor involvement.

$$RUSLE\ or\ USLE\ =\ [R] * [K] * [LS] * [C] * [P] \quad (1)$$

Where,
A = soil loss (t ha−1 yr−1),
R = rainfall erosivity factor (MJ mm ha−1 h−1, yr−1),
K = soil erodibility factor (t h MJ−1 mm−1),
LS = slope-length and slope steepness factor (dimensionless),
C = land management factor (dimensionless), and
P = conservation practice factor (dimensionless).

2.4.1 Rain Erosivity(R) factor

The rainfall erosivity factor (R) describes the erosivity of rainfall at a particular location based on the rainfall amount and intensity, and reflects the effect of rainfall intensity on soil erosion. The rainfall erosivity used in the RUSLE must quantify an effect of raindrop impact and explain the amount and rate of runoff associate with rainfall and its unit is expressed in MJ mm ha−1 h−1 yr−1.

For RUSLE: $R = 71.9 + 0.36P_a$(Subedi et al.,2017) (2)

For USLE : $R = 0.0483 * {P_a}^{1.61}$(Dangol & Mandal, 2023) (3)

Here, CHIRPS dataset is interpolated to match the resolution of the SRTM DEM.CHIRPS dataset provides daily rainfall data which when compare to the average rainfall data information available online shows similarity. So this data is said to be fairly accurate and conversely the rain erosivity factor.

2.4.2 Soil erodibility (K) factor

The soil erodibility factor (K) quantifies a soil's inherent susceptibility to erosion by rainfall and runoff, representing the amount of soil lost per unit of rainfall erosivity (R) under standard conditions. It is determined for a standard plot (22.13 m long, 9% slope, and continuous fallow) and is influenced by soil texture, organic matter content, structure, and permeability(Koirala et al., 2019).

For USLE and RUSLE:

$$\mathrm{K} = \mathrm{Fcsand} * \mathrm{Fsi} - \mathrm{cl} * \mathrm{Forgc} * \mathrm{Fhisand} * 0.1317 \tag{4}$$

Where,

$$\mathrm{Fcsand} = [0.2 + 0.3\exp(-0.0256\ \frac{\mathrm{SAN}}{1-\mathrm{SIL100})})], \tag{5}$$

$$\mathrm{Fsi} - \mathrm{cl} = [\frac{\mathrm{SIL}}{\mathrm{CLA+SIL}}]^{0.3} \tag{6}$$

$$Forgc = [1.0 - \frac{0.25\ CC}{\mathrm{C+exp(3.72-2.95\ C)}}] \tag{7}$$

Here, SAN, SIL and CLA are % sand, silt and clay, respectively; C is the organic carbon content; and SN1 is sand content subtracted from 1 and divided by 100. $Fcsand$= it gives a low soil erodibility factor for soil with coarse sand and a high value for soil with little sand content.

Fsi-cl = it gives a low soil erodibility factor with high clay to silt ration

Forgc = it is the factor that reduces soil erodibility for soil with high organic content.

Fhisand= it is the factor that reduces soil erodibility for soil with extremely high sand content.

Soil data obtained from NARC is extrapolated to the Kaski District using IDW in Arc Map.

2.4.3 Topographic (LS) factor

The topographic factor or Slope Length and Steepness Factors (LS) was created from two sub-factors: a slope gradient factor (S) and a slope-length factor (L); both of which are determined from the Digital Elevation Model (DEM). Slope-length and gradient is the important parameter in the soil erosion modeling, in calculating the transport capacity of overland flow (Surface runoff. The L factor represents the distance from the point where overland flow originates to the location where either deposition begins or runoff becomes concentrated in a defined channel. The S factor denotes the slope gradient. Together, the LS factor influences total sediment yield from a site, with yield being more sensitive to slope steepness than length. The input requirement for the creation of the topographic grid is a filled DEM. (Koirala et al., 2019). Here modified Winchester and smith equation((Wischmeier & Smith, 1978) by (Moore & and Wilson, 1992) was used to calculated LS factor with the NASA SRTM DEM dataset. Although the NASA SRTM DEM is an older global dataset, it remains highly relevant for this study, as topographic features such as slope and elevation change very little over time. Given the relatively stable terrain in Kaski District, the SRTM DEM continues to be a reliable and appropriate source for extracting topographic parameters required for soil erosion modeling.

For RUSLE:

$$LS = (\frac{FA*cellsize}{22.13})^m * (\frac{\sin(S)}{0.0896})^n \tag{8}$$

For USLE:

$$L = (\frac{FA*cellsize}{22.13})^m \tag{9}$$

$$S = 0.065 + 0.045 * s + 0.0065 * s^2 \tag{10}$$

$$LS = L * S \tag{11}$$

where,

FA = Flow Accumulation

Cell Size = 30m for SRTM DEM

S = Slope (in radians)

S = Slope (in percentage)

22.13 = Reference unit length (RUSLE standard)
0.0896 = Reference slope (9%)
m = 0.4
n = 1.3

2.4.4 Crop management (C) factor

The C-factor represents the influence of land cover (for non-croplands) and crop management practices (for croplands) on soil erosion relative to bare soil conditions. It quantifies the impact of vegetation and land use on erosion rates. Vegetation plays a crucial role in mitigating soil erosion by enhancing rainfall interception, promoting infiltration, and reducing the erosive force of raindrops. In this study, the C-factor is used to assess how different land cover types contribute to soil erosion risk.(Koirala et al., 2019). Here for calculation of C factor, formula used by (Vatandaşlar & Yavuz, 2017) for RUSLE and Cfactor value for LULC for USLE (Koirala et al., 2019; Panagos et al., 2015)

For RUSLE:

$$C = 0.431 - 0.805 * \mathrm{NDVI} \quad (12)$$

Here, the NDVI for C value is calculated using the band information Sentinel 2 image. C value is further refined by masking clouds as much as possible using automated cloud and shadow removal step using the 'Q60' band and masking of water and snow NDVI value for water and snow.

For USLE: C factor value is assigned to the land cover class of ICIMOD LULC of 2022.

Table 7: C factor value

Land cover	C factor value
Water	0
Glacier	0
Snow	0
Forest	0.03
Riverbed	0.01
Built-up Area	0
Cropland	0.03
Bare soil	0.45
Bare Rock	0.1
Grassland	0.03
Other wooded land	0.03

2.4.5 Support practice (P) factor

The Support Practice Factor (P-factor) in the RUSLE model reflects the effectiveness of erosion control practices such as contour farming, terracing, and strip cropping in reducing soil loss. Ranging from 0 (maximum erosion control) to 1 (no conservation measures), this factor adjusts erosion estimates based on implemented land management strategies. In Nepal's mountainous terrain, where terraced agriculture predominates, these systems are modeled similarly to contour farming due to their comparable ability to intercept runoff and minimize soil displacement. This approach allows for practical erosion rate assessments while acknowledging terraces as a traditional yet effective conservation practice in steep-slope farming systems(Renard et al., 1994; Wischmeier & Smith, 1978). The P-factor thus serves as a critical parameter for evaluating how agricultural interventions can mitigate soil erosion under varying topographic and management conditions. For our study, P factor is based on the slope of the obtained from SRTM DEM. Here, slope is used because it is an approach used for overall Nepal(Koirala et al., 2019) as well as for hill regions of Nepal(K. Joshi, 2023; Thapa, 2020) to emulate the contour farming. The value of p factor is based on the flowing table(Koirala et al., 2019)

Table 8: P factor value based on slope

Slope %	Contouring
0-7	0.55
7-11.3	0.60
11.3-17.6	0.80
17.6-28.7	0.95
>28.7	1

3. Results and Discussion

3.1 Results

Below are the results of the factors maps of each factors of the USLE/ RUSLE models showing the ranges of each factor for each Soil erosion Model.

The result of RUSLE and USLE five erosion factors calculation for Kaski District revealed distinct spatial patterns. R-factor showed erosivity values ranging 774-2082 MJ mm ha^{-1} h^{-1} yr^{-1} (RUSLE) and 552-1970 MJ mm ha^{-1} h^{-1} yr^{-1} (USLE), with higher rainfall impacts in southern areas. Both models identified similar C-factor distributions (0-0.56 RUSLE, 0-0.45 USLE), reflecting varied land cover from dense forests to bare soil areas. The LS-factor reached 58.08 (RUSLE) and 55.06 (USLE) on steep slopes, while K-factor values remained consistent (0.0286-0.0406). Final erosion maps displayed comparable spatial patterns between models, with RUSLE estimating 0->80 t ha^{-1} yr^{-1} and USLE showing slightly higher values in the same classification ranges. The P-factor (0.55-1.0) indicated varying effectiveness of conservation practices across the district based on the slope map of the Kaski district.

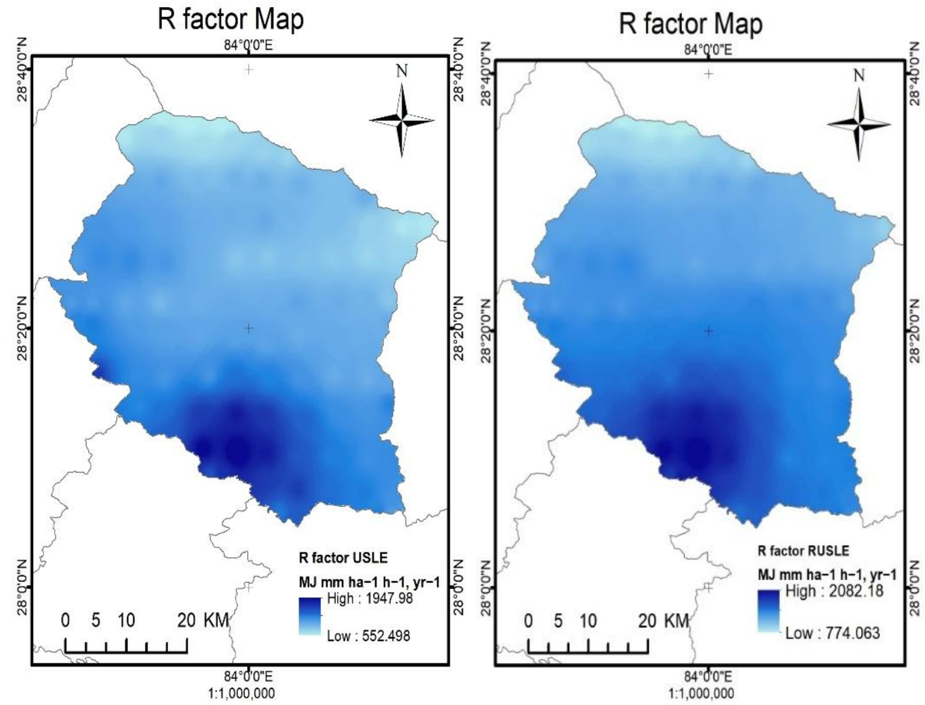

Fig. 34: R factor Map

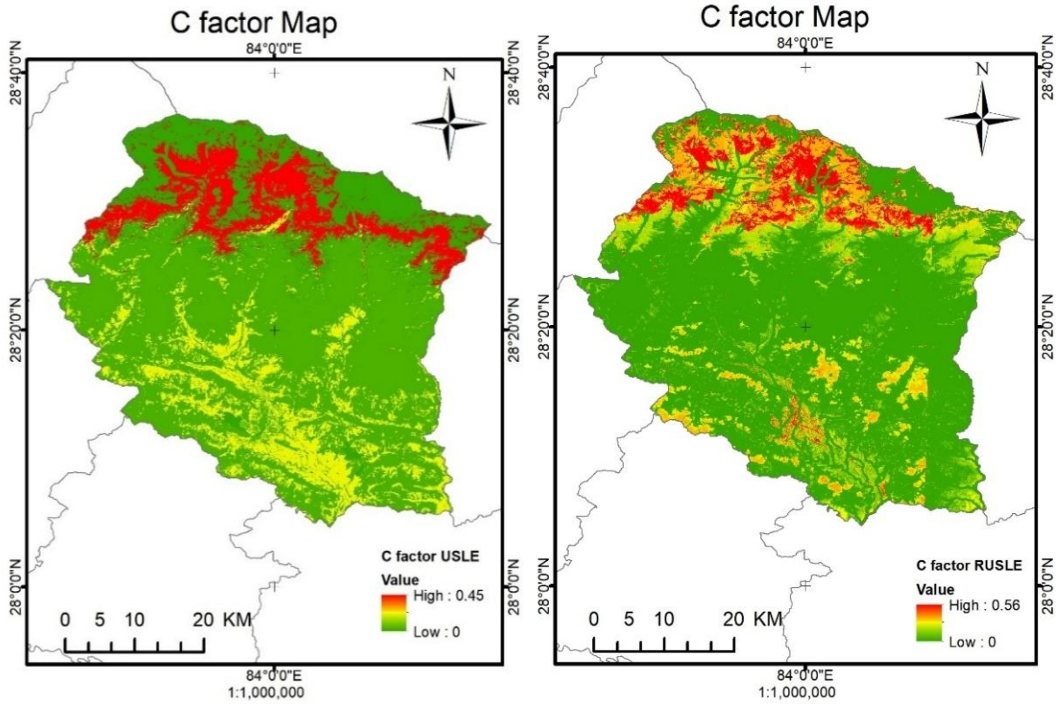

Fig. 35: C factor Map

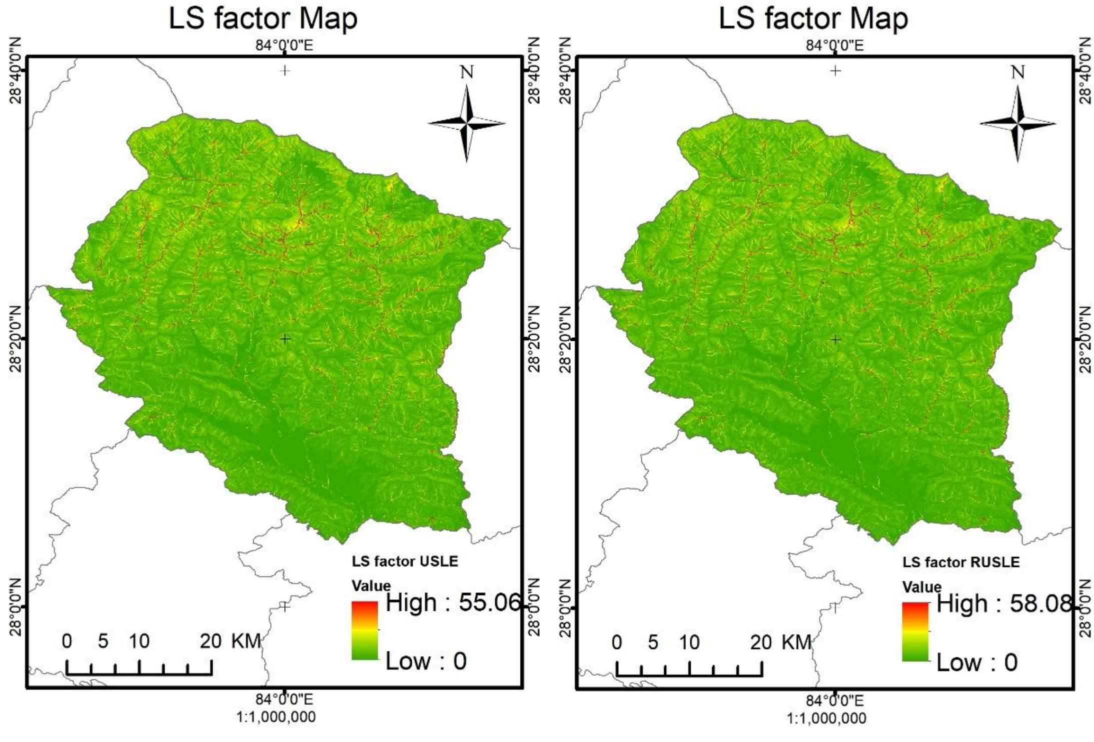

Fig. 36: LS factor Map

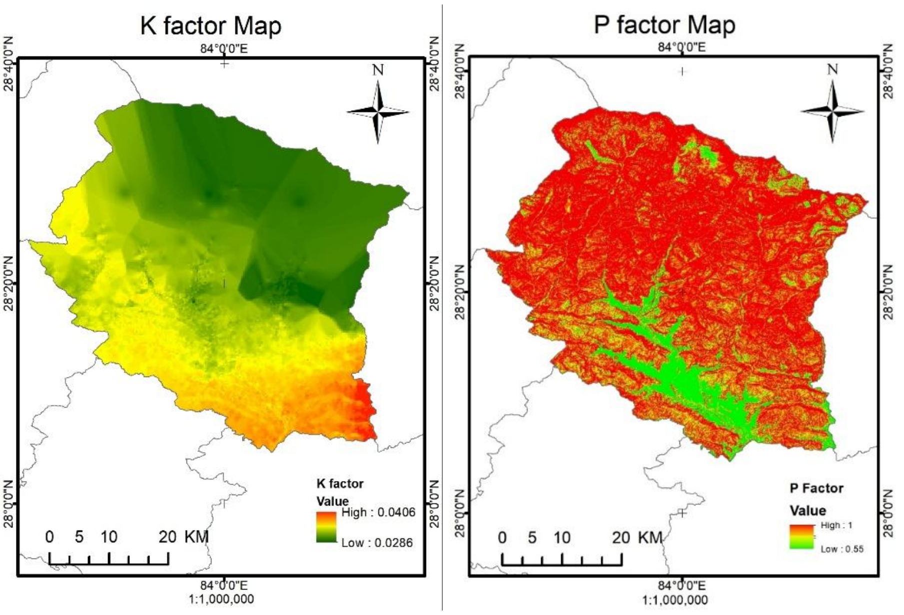

Fig. 37: K and P factor Map

Here, the Soil erosion value for RUSLE ranges for 0 to 269 t ha−1 yr−1 for RUSLE while the USLE model shows the ranges of 0 to 289 t ha−1 yr−1.

3.2 Discussion

Our soil erosion assessment using the RUSLE and USLE models revealed that the USLE produced higher soil erosion estimates than the RUSLE, likely due to differences in factors' formula and datasets used in our study. For Kaski District, our results closely align with the findings of Koirala et al. (2019), showing comparable erosion ranges and spatial distribution: characterized by lower estimates in the southern regions and progressively higher erosion rates toward the Annapurna Himalayan ranges in the north. This consistency is evident in the distribution of soil loss across the landscape, as reflected in our model's output.

While direct field verification was not feasible due to a lack of contemporary ground data—a recognized gap of this study—we adopted the next best approach by comparing our model's outputs with established erosion patterns from studies conducted in the past. Phewa watershed(Bista & Basnet, 2017) confirms that our model's predictions match well with existing patterns. Additionally, when compared to the RUSLE-based study of the Kali Gandaki Basin (Subedi et al., 2017), our results show comparable erosion rates (~20 t ha^{-1} yr^{-1}), particularly in areas with similar topography and land use. While no dedicated USLE model studies exist specifically for Kaski district soil erosion estimation, comparison reveals that USLE produces soil erosion estimates comparable to RUSLE results in this region. The similarity in outputs suggests USLE remains a usable erosion prediction model for Kaski and similar mountainous areas, particularly given matching land cover characteristics, geographic distribution, and weather patterns. This agreement between models persists despite USLE's typically higher estimates, indicating its robustness for applications agreements across.

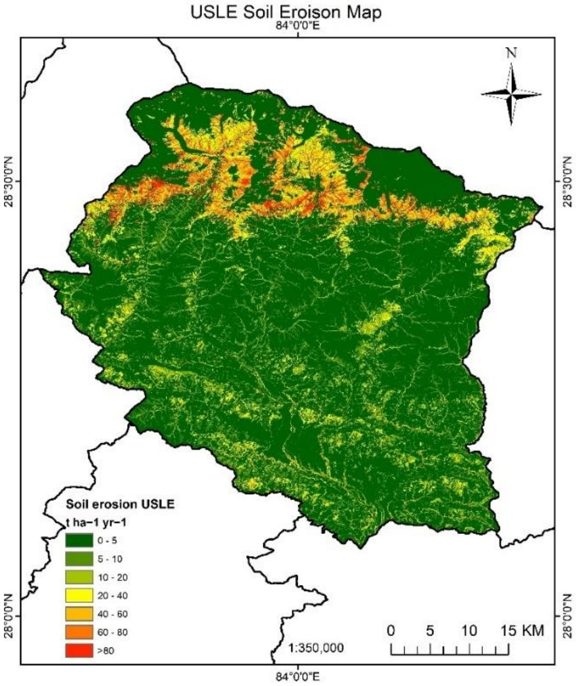

Fig. 38: USLE soil erosion map

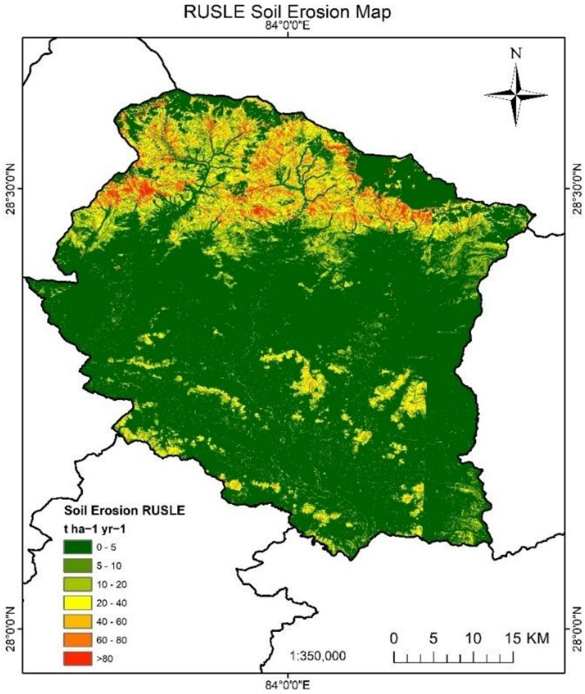

Fig. 39: Soil Erosion Map RUSLE

4. Conclusion

This study concludes that the RUSLE and USLE models effectively estimate soil erosion in Kaski District, with results consistent with previous research despite limited field validation. The erosion maps generated provide actionable insights for stakeholders, enabling targeted conservation strategies in high-risk zones such as steep slopes and deforested areas. Local authorities can use these findings to prioritize interventions like terracing, afforestation, and check dam construction, while land-use planners can integrate erosion risk data into support for sustainable development policies. Additionally, the results support watershed management initiatives by identifying sediment source areas critical for downstream water quality. By bridging research and practical application, this study offers a foundation for evidence-based soil conservation and land-use planning in Nepal's mountainous regions. The methodology's success also suggests strong potential for application and scalability in other Nepalese districts and regions facing similar data. Approach adopted in this study could be readily adapted for erosion modeling in neighboring mid-hill districts as well as other regions with comparable geomorphic conditions, though careful validation would be needed when extending to areas with difference in climatic and topology.

References

Bajracharya, R. M., & Sherchan, D. P. (2009). Fertility status and dynamics of soils in the Nepal Himalaya: A review and analysis. *Soil Fertility*, 111–135.

Bhattarai, R., & Dutta, D. (2007). Estimation of Soil Erosion and Sediment Yield Using GIS at Catchment Scale. *Water Resources Management*, *21*(10), 1635–1647. https://doi.org/10.1007/s11269-006-9118z

Bista, J. B., & Basnet, K. (2017). *Assessment of Land Use Land Cover Change Impact on Soil Loss from Phewa Lake Watershed, Pokhara, Nepal*.

Borrelli, P., Robinson, D. A., Fleischer, L. R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V., Bagarello, V., Oost, K. V., Montanarella, L., & Panagos, P. (2017). An assessment of the global impact of 21st century land use change on soil erosion. *Nature Communications*, *8*(1), 2013. https://doi.org/10.1038/s41467-017-02142-7

Chalise, D., Kumar, L., & Kristiansen, P. (2019). Land Degradation by Soil Erosion in Nepal: A Review. *Soil Systems*, *3*(1), Article 1. https://doi.org/10.3390/soilsystems3010012

Dahal, R. (2020). Soil Erosion Estimation Using RUSLE Modeling and Geospatial Tool: Case Study of Kathmandu District, Nepal. *Forestry: Journal of Institute of Forestry, Nepal*, *17*, 118–134. https://doi.org/10.3126/forestry.v17i0.33627

Dangol, S., & Mandal, U. (2023). Application of Geo-informatics for Soil Erosion Mapping. *Journal on Geoinformatics, Nepal*, 1–9. https://doi.org/10.3126/njg.v22i1.55116

Gardner, R., & Gerrard, J. (2001). SOIL LOSS ON NONCULTIVATED LAND IN THE MIDDLE HILLS OF NEPAL. *Physical Geography*, *22*(5), 376–393. https://doi.org/10.1080/02723646.2001.10642750

Gelal, D., Timilsina, S., Ayer, S., Bhatta, K. P., Manandhar, B., & Maharjan, M. (2024). Soil erosion estimation in the Bagmati River basin of Nepal using RUSLE modeling to assess priority areas for conservation. *Journal of Sedimentary Environments*, *9*(3), 727–744. https://doi.org/10.1007/s43217-024-00189-3

Ghimire, C. P., Bonell, M., Bruijnzeel, L. A., Coles, N. A., & Lubczynski, M. W. (2013). Reforesting severely degraded grassland in the Lesser Himalaya of Nepal: Effects on soil hydraulic conductivity and overland flow production. *Journal of Geophysical Research: Earth Surface*, *118*(4), 2528–2545. https://doi.org/10.1002/2013JF002888

Joshi, K. (2023). Estimation of soil erosion using the Revised Universal Soil Loss Equation (RUSLE) in Relation to Landslides in Western Mid-hills of Nepal. *Research Square (Research Square)*. https://www.academia.edu/108554119/Estimation_of_soil_erosion_using_the_Revised_Universal_Soil_Loss_Equation_RUSLE_in_Relation_to_Landslides_in_Western_Mid_hills_of_Nepal

Joshi, P., Adhikari, R., Bhandari, R., Shrestha, B., Shrestha, N., Chhetri, S., Sharma, S., & Routh, J. (2023). Himalayan watersheds in Nepal record high soil erosion rates estimated using the RUSLE model and experimental erosion plots. *Heliyon*, *9*(5), e15800. https://doi.org/10.1016/j.heliyon.2023.e15800

Koirala, P., Thakuri, S., Joshi, S., & Chauhan, R. (2019). Estimation of Soil Erosion in Nepal Using a RUSLE Modeling and Geospatial Tool. *Geosciences*, *9*(4), 147. https://doi.org/10.3390/geosciences9040147

Lal, R. (2001). Soil degradation by erosion. *Land Degradation & Development*, *12*(6), 519–539. https://doi.org/10.1002/ldr.472

Moore, I. D., & and Wilson, J. P. (1992). Length-slope factors for the Revised Universal Soil Loss Equation: Simplified method of estimation. *Journal of Soil and Water Conservation*, *47*(5), 423–428. https://doi.org/10.1080/00224561.1992.12456740

Panagos, P., Borrelli, P., Meusburger, K., Alewell, C., Lugato, E., & Montanarella, L. (2015). Estimating the soil erosion cover-management factor at the European scale. *Land Use Policy*, *48*, 38–50. https://doi.org/10.1016/j.landusepol.2015.05.021

Renard, K. G., Laflen, J. M., Foster, G. R., & McCool, D. K. (1994). The Revised Universal Soil Loss Equation. In *Soil Erosion Research Methods* (2nd ed.). Routledge.

Thapa, P. (2020). Spatial estimation of soil erosion using RUSLE modeling: A case study of Dolakha district, Nepal. *Environmental Systems Research*, *9*(1), 15. https://doi.org/10.1186/s40068-020-00177-2

Vatandaşlar, C., & Yavuz, M. (2017). Modeling cover management factor of RUSLE using very high-resolution satellite imagery in a semiarid watershed. *Environmental Earth Sciences*, *76*(2), 65. https://doi.org/10.1007/s12665-017-6388-0

Wischmeier, W. H., & Smith, D. D. (1978). *Predicting Rainfall Erosion Losses: A Guide to Conservation Planning*. Department of Agriculture, Science and Education Administration.