GIS and remote sensing-based assessment of soil erosion risk using RUSLE model in South-Kivu province, eastern, Democratic Republic of Congo

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ABSTRACT
Soil erosion risk assessment in South-Kivu longs for the colonial epoch, while the province faces the problem of extreme degradation of land in the form of soil erosion. Thus, the study attempts to assess the soil erosion at the province level using the Revised Universal Soil Loss Equation (RUSLE) in conjunction with the Geographical Information System (GIS), and remote sensing data. The estimated total soil erosion was 2.084 million tons; with an annual average of 138.2 t ha\textsuperscript{-1}yr\textsuperscript{-1}. Moreover, the soil loss greater than 100 t ha\textsuperscript{-1}yr\textsuperscript{-1} accounts for 45.2\% of the total erosive land. The soil erosion worsening nearly the entire territories range between 87 t ha\textsuperscript{-1}yr\textsuperscript{-1} in Shabunda to 248 t ha\textsuperscript{-1}yr\textsuperscript{-1} in Uvira. Under high aggressiveness of rainfall with mean of 1857.19 mm/yr, the highest rate found in Perennial crop, Trees, and Cropland in contrast to Shrub and closed Forest was mainly due to the mean slope of 22\% found in the former Land cover categories compared to 17\% of Shrubland and closed Forest. The adoption of terracing could reduce by 76\% the current rate of cropland i.e., from (162.12 t ha\textsuperscript{-1}yr\textsuperscript{-1} to 38 t ha\textsuperscript{-1}yr\textsuperscript{-1}). Therefore it is strongly recommended.

1. Introduction
Soil erosion is the most widespread form of land degradation and the main source of water pollution worldwide (Arabameri et al. 2020; Band et al. 2020). About 85\% of land degraded globally is due to soil erosion, causing a decline in crop yield up to 17\% (Oldeman et al. 1991) and lead to 10 million hectare of land abandonment each year (Faeth and Crosson 1994; Pimentel et al. 1995), and cause many off-site
problems such as reduction of the storage capacity of reservoirs at a rate of about 1% per year (Mahmood 1987). Consequently, threatens the stability and health of society, socioeconomic welfare and accentuates malnutrition (Panagos et al. 2015; Chowdhuri et al. 2020; Roy et al. 2020). As it is presently estimated that more than one billion persons, or one out of every seven people on the planet, is hungry and/or malnourished (Idso and Idso 2011), a problem likely to become extreme as the world population is estimating to reach 9.7 billion by 2050 (Lutz and K C, 2010).

The soil erosion among other natural geohazards is triggered by natural factors such as the rainfall intensity, marginal topographic features, and the fragility of soil to detachment during intense rainfall (Clark 1987; Renard and Freimund 1994; Meusburger et al. 2012; Choudhari and Chaudhari 2019; Pal et al. 2020) however, it is accelerated by anthropogenic factors such as population growth, forest clearing, and poverty among other (Jong 1994; Pimentel et al. 2005; Pimentel and Burgess 2013; Esa et al. 2018). The only way to preserve biodiversity, protect natural resources from depletion while keeping the soil continuously productive, is through sustainable planning and better management (Choudhari and Jadhav 2019; Roy et al. 2020; Saha et al. 2020; Uwemeye et al. 2020).

Unfortunately, The DRC experienced unsustainable land use manifested by a major change in land cover such as the expansion of agricultural land at the expense of forest in response to the pressure of population growth (Molinario et al. 2020). Additionally, the high poverty estimated at 63.3% of the total population (World Bank 2018) associated with long-term political instability, violent conflict during the past three decades (Kabantu et al. 2018). Consequently, there was no adequate planning and policies (Heri-Kazi and Bielders 2020), therefore, accelerating the ecosystem encroachment, and environmental deterioration.

South-Kivu province like other provincial administrative entities in DRC is potentially challenged by various forms of land degradation (Bitijula and Lal 1983; Heri-Kazi and Bielders 2018). Due to the fragile socio-economic status of its population characterized by the subsistence farming for smallholder farmers often on a marginal slope with poor conservation measures (Ocimati et al. 2020). Besides, the rapid food demand from the growing population estimated at 6 million (OCHA 2019b). Thereby led to massive exploitation of available lands and overgrazing, exposing the province to serious degradation of land in the form of soil erosion by water and nutrient depletion (Lunze 2000), pose a challenge to agriculture productivity (Muhindo 2015), and ultimately, accentuated the food insecurity in the province estimated at around 60% (Walangululu et al. 2010).

A good understanding of the spatial patterns of soil erosion through risk assessment is the key element toward sustainable planning and better management (Prasannakumar et al. 2012; Maliqi and Singh, 2019; Kumar Pradhan et al., 2020). Despite the above pieces of evidence, the risk assessment of soil erosion at a provincial scale longs for the colonial epoch (Heri-Kazi and Bielders 2020). So far, only a few studies were conducted the soil erosion assessment at catchment and plot levels (Kulimushishi 2016; Heri-Kazi and Bielders 2018). Meanwhile, South-Kivu like other entities in DRC is still facing a research shortage regarding hazard modeling.
The Revised Universal Soil Loss Equation (RUSLE) is a flexible model in assessing erosion of soil because of data availability, simple to apply, and easy to integrate with Geographical Information System (GIS) interface using remote sensing (Rs) data. RUSLE model combined with GIS and Rs selected for the present study was effectively adapted widely in various landscapes (Cox and Madramootoo 1998; He 2003; Nekhay et al. 2009; Zhang et al. 2013; Duarte et al. 2016; Rejani et al. 2016) and demonstrated the applicability of GIS and remote sensing to model the magnitude and spatial distribution of soil erosion compared to the conventional methods which are complex, time-consuming and costly.

Therefore, focusing on key contributory factors, it’s worth to gain an overview of the current South-Kivu erosion map profile by conducting a quantitative assessment of soil erosion at a provincial scale and identify the soil erosion hotspot areas. The results provided vital information previously unavailable that will guide planners, decision-makers, and stakeholders to the most vulnerable areas, and in the same line suggest adequate soil conservation practice. Given the above aspects, the objectives of the present study were: (1) To assess the potential and actual soil erosion risk in South-Kivu; (2) estimate the territory’s level of soil erosion rate and explore the spatial relationship between soil erosion and LULC and slope categories; and (3) to assess the potential effect of terracing, strip-cropping, and contouring on soil erosion reduction in agricultural land.
2. Materials and methods

2.1. Description of the study area

South-Kivu is among the twenty-six provinces of the DRC that covers about 64216 Km² (Figure 1) approximately 2.73% of the total national land area (OCHA 2019a). The total population is about 6 million (OCHA 2019b). South-Kivu lies between (-1.5836°S to -5.0103°S) Latitude and (26.8106°E to 29.3890°E) longitude. It borders Rwanda, Burundi, and Tanzania to the east; North Kivu province to the north, Maniema province to the west, and Tanganyika province to the south.

The province is subdivided into eight administrative territories namely (Shabunda, Mwenga, Fizi, Kalehe, Uvira, Walungu, Kabare, and Idjwi) including the city of Bukavu (Figure 1(c)). The climate is equatorial and tropical (UNDP 2009), characterized by a mean annual rainfall of 1500–1800 mm per year (Farrow et al. 2006) and the average annual temperature varies between 11° and 25°C (UNDP 2009). The elevation fluctuates from 512 to 3464 meters above the sea level (masl) and decreases from east to west. The rainfall in South-Kivu allows crop growth during two subsequent seasons. ‘A’ season allows crop cultivation from mid-September to mid-January, and ‘B’ season allows crop cultivation from mid-February to mid-June (Walangululu et al. 2010).

According to FAO/IIASA/ISRIC/ISS-CAS/JRC (2013), South-Kivu is dominated by seven major soil groups: Haplic Acrisols, Humic Cambisols, Humic Ferrasol, Luvic Phaeozems, Mollic Fluvisols, Vertisols, and Gleyic Solonchaks. The gentle slopes are found in the eastern part especially in Lake Kivu and Lake Tanganyika, and in the western part bordering Maniema province, while the other parts are characterized as steep and very steep.

2.2. Land use land cover

The land cover map was extracted from the more recent product (2018) of the European Space Agency (ESA) climate change initiative land cover project (CCI-LC) (cds.climate.copernicus.eu). The global land cover delivered at a spatial resolution of 300 m, counts 22 classes defined using the FAO land cover classification system (Townshend et al. 2008) with an overall accuracy of 74.4%. The land cover of 2018 was produced from different images processing, more details can be found from (ESA 2017) including the classification of Medium Resolution Imaging Spectrometer Full reduced resolution (MERIS) time series from 2003 to 2012, back and up-dated based on time series from AVHRR (1992–1999), SPOT-VGT (1998–2012), PROBA-V (2013–2019) and Sentinel-3 OLCI (2013–2019). The dataset was used in many studies and at various scales, and both confirmed the potential utility of the CCI-LC dataset in monitoring the land cover (Pérez-Hoyos et al. 2017; Mousivand and Arsanjani 2019). The global raster dataset delivered in NetCDF4 format was subset to Region of Interest (ROI) using South-Kivu geo-coordinates; converted to Geotiff format and re-projected to World Geodetic System (WGS84)/Universal Transverse Mercator (UTM) Zone 35S using ESA SNAP 6.0 (http://step.esa.int).

South-Kivu encompasses 21 land cover classes defined under FAO’s land cover classification system (LCCS), these classes were later reclassified based on local knowledge. After the reclassification, ten classes were obtained: Closed forest, Cropland,
Grassland, Open forest, Perennial crop, Shrubland, Tree cover, urban area, Waterbodies, and Wetland (Table 1 and Figure 2). CCI-LC was also used to separate erosive and non-erosive prone areas, hence three classes were not considered in soil erosion assessment such waterbodies, wetland, and urban area (Panagos et al. 2015; Karamage et al. 2017; Nambajimana et al. 2019) shared around 10% of the total South-Kivu land area.

2.3. The revised soil loss equation

The model used in this study was first developed by Wischmeier and Smith (1978) and improved later by Renard et al. (1997). RUSLE (Equation 1) predict the long term average soil erosion rate by the use of five explanatory variables namely: Erosivity factor (R), Erodibility factor (K), Slope length and Slope steepness factor (LS), Cover management factor (C), and Land management factor (P) (Pal and Chakrabortty 2019a). Two soil erosion risk maps were determined to identify the area of greatest vulnerability; the potential soil loss risk map comprises only the multiplication of the natural or less controlled variables \(\frac{R}{C^2} \times \frac{K}{C^2} \times LS\), as well as the actual soil erosion risk map that considers the five RUSLE factors given in the Equation (1) (both natural and human-induced or controlled variables).

\[
A = R \times K \times LS \times C \times P
\]

where A is the total annual soil loss t ha\(^{-1}\) yr\(^{-1}\), R is the erosivity factor in MJ mm ha\(^{-1}\) h\(^{-1}\) yr\(^{-1}\), K is the erodibility factor in tons ha h ha\(^{-1}\) MJ\(^{-1}\) mm\(^{-1}\), LS is the Slope length and steepness (Dimensionless), C represents the Cover management (Dimensionless) and P is the land management factor (Dimensionless).

The inputs used to compute the above parameters are given in Table 2 below:

| Land cover types   | Area (ha) | Area (%) |
|--------------------|-----------|----------|
| Closed forest      | 3705263.2 | 57.7     |
| Cropland           | 1110936.8 | 17.3     |
| Grassland          | 179804.8  | 2.8      |
| Open forest        | 229893.28 | 3.58     |
| Perennial crop     | 12843.2   | 0.2      |
| Shrubland          | 186226.4  | 2.9      |
| Trees              | 327501.6  | 5.1      |
| Urban area         | 7705.92   | 0.12     |
| Waterbodies        | 520149.6  | 8.1      |
| Wetland            | 141275.2  | 2.2      |
| South-Kivu         | 6421600   | 100      |

The datasets were pre-processed and analyzed in the spatial analyst extension of ArcGIS software (Environmental Systems Research Institute (Esri) Inc., Redlands, CA, USA). And ESA SNAP 6.0 (http://step.esa.int) has been used to preprocess the CCI-LC product, such as subset the global raster to Region of Interest (ROI) using South-Kivu geo-coordinates; converted the NetCDF4 format to Geotiff format. The products were first projected to the same UTM Zone 35S coordinate system and resampled to a common spatial resolution of 30 m of pixel size as the most suitable grid resolution to produce soil erosion risk maps of high resolution.
To facilitate the analysis, soil erosion maps were reclassified into four severity classes: moderate (0–100 t ha\(^{-1}\) yr\(^{-1}\)); high (100–200 t ha\(^{-1}\) yr\(^{-1}\)); very high (200–300 t ha\(^{-1}\) yr\(^{-1}\)); and extremely high (>300 t ha\(^{-1}\) yr\(^{-1}\)) adapted from (Karamage et al. 2016). Low erosion class was not considered in this study, the low erosion class is combined with moderate severity class.

2.3.1. Erosivity factor (R)

The erosivity factor (R) is defined as the long-term annual average of the product of event rainfall kinetic energy and the maximum rainfall intensity of 30 minutes. It simply reflects the rainfall capacity to cause erosion (Toy et al. 2002).

Figure 2. Land cover types. Source: Author.

Table 2. Type, coordinate system, resolution and source of dataset used in this study.

| Name        | Coordinate system | Resolution | Source                                      |
|-------------|-------------------|------------|---------------------------------------------|
| CHIRPS      | WGS84             | 0.05°      | Funk et al. 2015                           |
| AfSIS       | WGS84             | 250 m      | Hengl et al. 2015                          |
| SRTM V4     | WGS84             | 3 arc second | Jarvis et al. 2008                        |
| MODIS NDVI  | WGS84             | 250 m      | ladsweb.modaps.eosdis.nasa.gov             |
| CCI-LC      | WGS84             | 300m       | cds.climatic.copernicus.eu                 |
| HWSD V1.2   | WGS84             | 30 arc second | FAO/IIASA/ISRIC/ISS-CAS/JRC 2013         |

CHIRPS: Climate Hazards Group InfraRed Precipitation; AfSIS: Africa Soil Information Service; SRTM V4: Shuttle Radar Topographical Mission Version 4; MODIS NDVI: Moderate Resolution Imaging Spectroradiometer Normalized Difference Vegetation Index; CCI-LC: Climate change initiative land cover project; HWSD V1.2: Harmonized World Soil Database version 1.2.
The estimation of erosivity factor using the empirical Wischmeier and Smith (1978) method is not used in the majority of cases because of the non-availability of the required number and depth of storm erosivity index (EI) (Prasannakumar et al. 2012) such as the poor data context of the DRC. These data are limited to only a few stations around the world (Wijesundara et al. 2018; Kidane et al. 2019). Alternatively, monthly rainfall data can be used as a proxy (Renard and Freimund 1994; Xin et al. 2011). As a result, several methods were then developed to estimate R-factor values based on long-term mean annual rainfall (Chakrabortty et al. 2020). The present study used the relationship (Equation (2)) developed by Lo et al. (1985). The same equation was used in regions having similar landscapes (Karamage et al. 2016, 2017).

\[
R = 38.46 + (3.48 \times P)
\]  

(2)

where R is the erosivity factor expressed as MJ mm ha\(^{-1}\) h\(^{-1}\) yr\(^{-1}\), and P is the long-term mean annual precipitation in mm.

2.3.2. Erodibility factor (K)
The soil erodibility expresses the susceptibility of soil properties (physical, chemical, and biological) to detachment and transport by water during a storm event (Wischmeier and Smith 1978).

The soil map derived from the Harmonized World Soil Database (HWSD) has shown that South-Kivu comprises seven major soil groups given in descending order according to their spatial coverage in percent, namely: Acrisols (48.64%), Cambisols (31.82%), Ferrasols (9.92%), Phaeozems (0.9%), Fluvisols (0.26%), Vertisols (0.23%), and Solonchaks (0.16%), and the remaining surface is occupied by waterbodies as adapted from the revised FAO 1990 soil map legend (FAO/IIASA/ISRIC/ISS-CAS/JRC 2013).

Soil erodibility is measured based on relevant soil properties that make the soil susceptible to erosion, such as soil texture, organic matter content, structure, and permeability (Renard et al. 1997; Panagopoulos et al. 2006; Chakrabortty et al. 2020). These properties normally vary in different soil type thus the susceptibility to erosion vary within different soil type (Adornado et al. 2009; Sharma 2010), for instance, the soil with high clay and sand are more resistant than the soil with high silt easily detached, apart from these, the organic matter increases the cohesiveness thus reduce the erosivity effect to the soils (Renard et al. 1996). The present study focused on available soil texture representing the percent of sand, silt, and clay along with the organic matter the most important soil properties (Claessens et al. 2008; Tamene and Le 2015).

Alternatively, attempts have been made to estimate K factor values based on soil color (Bono and Seiler 1984), and soil texture (sand, silt, and clay) in combination with organic matter (Stone and Hilborn 2012) derived from various global and regional soil databases. The study used the relationship (Equation (3)) proposed by Williams (1995).

\[
KUSLE = f_{csand} \times f_{cl-si} \times f_{orgC} \times f_{hisand} \times 0.1317
\]  

(3)
\[
K_{USLE} = \left[ 0.2 + 0.3\exp(-0.0256 \text{SAN}(1-\text{SIL}/100)) \right] \times \left( \frac{\text{SIL}}{\text{CLA} + \text{SIL}} \right)^{0.3} \\
\times \left[ 1-(0.0256 C/(C + \exp(3.72 - 2.95 C))) \right] \\
\times \left[ 1-(0.7 \text{SAN1/SN1} + \exp(-5.51 + 22.9\text{SN1})) \right] \times 0.1317 
\]  

(3a)

where SAN represents the percentage of sand content (0.05–2.00 mm of diameter); SIL denotes the percentage of silt content (0.002–0.05 mm of diameter); CLA represents the percentage of the clay content (<0.002 mm diameter); C is the percentage of the organic carbon and SN1 = 1-(SAN/100). A factor of 0.1317 was used to convert the US units into the international system units (Renard et al. 1997).

2.3.3. Slope length and slope steepness factors (LS)

The topographic factor accounts for the overall contribution of slope length and slope gradient on soil erosion (Wischmeier and Smith 1978). The factor is a reference ratio of soil loss under a standard slope length of 22.13 m and the steepness of 0.09 rad about (5.14° or 9%) of a USLE plot unit (Renard et al. 1997). Therefore, it plays an important role in increasing the kinetic energy of the runoff by accelerating the accumulation of runoff toward the downslope (Pal and Shit 2017)

The slope map and upslope contributing area based on Digital Elevation Model (DEM) substitute the standard slope steepness and slope length measurement (Panagos et al. 2015). The present study used the DEM extracted from Shuttle Radar topographical mission (SRTM) 3 arc second version 4 provided by (Jarvis et al. 2008). SRTM was preferred because of its large area coverage, free cloud, and recommended for its high vertical accuracy and the better spatial relationship of topographic features as a literature report (Farr and Kobrick 2000).

Spatial analyst extension of ArcGIS software (Environmental Systems Research Institute (Esri) Inc., Redlands, CA, USA) was used to pre-process the DEM by removing artificial sinks and further used the corrected DEM to compute the initial inputs, such as slope in degree, flow direction and flow accumulation the main inputs used for LS estimation. Then, the raster calculator tool located in spatial analyst extension in ArcGIS software was used to compute separately L-factor (Equation (4)) applying the relationship proposed by Desmet and Govers (1996). And S-factor was determined after McCool et al. (1987) recommendation (Equation (5)). For consistency purposes, the resulting slope and upslope factor were resampled to 30 m cell size.

\[
L_{i, j} = \frac{\left( A_{(i,j), \text{in}} + D^2 \right)^{(m+1)}}{x_{(i,j), \text{in}}^m \times D^{(m+2)} \times 22.13^m} \text{ where } m = \frac{\beta}{1 + \beta} 
\]

(4)

and \( \beta = \frac{\sin \theta}{0.0896 - 3(\sin \theta)^{0.8} + 0.56} \)

\[
S = \left\{ \begin{array}{l}
10.8 \times \sin \theta_{(i,j)} + 0.3, \tan \theta_{(i,j)} < 9\
10.8 \times \sin \theta_{(i,j)} + 0.3, \tan \theta_{(i,j)} < 9
\end{array} \right\} 
\]

(5)
where $A_{i,j}$ is replaced by the flow accumulation, which indicates the accumulated upslope contributing area per unit cell; $D$ is the grid cell size in (meter); $m$ is a variable slope length exponent related to the $\beta$, $x_{i,j} = (\sin a_{i,j} + \cos a_{i,j})$; $\beta$ is ratio of rill to interrill erosion; $\theta$ is the slope angle in degree.

### 2.3.4. Cover management (C)

C-factor estimates the difference in predicted soil erosion due to variability in cropping and surface cover management (Bull et al. 2003; Tamene and Le 2015). The rate of soil erosion often varies within the different cover and crop management (Jong 1994; Esa et al. 2018). C factor values range from 0 to 1, a value near zero witnesses a well-protected and dense vegetation, whereas values higher than 0.4 indicate the least covered surface and 1 denoting barren land highly vulnerable to rill erosion (Adediji et al. 2010; Pimentel and Burgess 2013).

**Figure 3.** RUSLE factors (a) Erosivity factor, (b) Erodibility factor, (c) Slope length and steepness, (d) Cover management factor. Source: Author.
Two methods are commonly used to estimate C-factor values, first C-factor is estimated based on Normalized Difference Vegetation Index (NDVI) derived from satellite remote sensing (Van Knijff et al. 2000; Pal and Chakrabortty 2019b) and second, researchers attempt to assign fixed values to different LULC based on expert knowledge (Nam et al. 2003; Panagos et al. 2015). As stated by Jiang et al. (2014) assigning fixed C values sometimes challenge due to the spatiotemporal variation in surface cover patterns, consequently, NDVI method was preferred for the following reasons:

NDVI accounts for the spectral difference of green vegetation in the Near Infrared (NIR) and Red (R) portions of the electromagnetic spectrum (Zitao et al. 2008). This vegetation index is strongly correlated with the amount and level of green biomass (Hansen et al. 2000; Prasannakumar et al. 2012). Various researchers including (Van Knijff et al. 2000; Rao et al. 2019) reported that NDVI is a suitable indicator to recognize features like vegetation coverage and can give the seasonal trend of vegetation.

Since the cover management is closely related to the interception of rainfall energy by crops during the growing season (Morgan 1995), it is recommended to integrate into the equation the seasonal variation of crops production along with the variation of rainfall fraction in each season (Maqsoom et al. 2020). The mean time series NDVI for the two growing seasons of 2019 has taken into account six representative months (March, April, May, September, October, and November) when the erosion is active and the vegetation at a peak.

The spatial distribution of C-factor values as can be seen in Figure 3(d) was calculated using Equation (6) proposed by Durigon et al. (2014) by the means of MODIS NDVI obtained from (ladsweb.modaps.eosdis.nasa.gov) processed in a raster calculator located in the spatial analyst extension of ArcGIS software. This relationship was used in (Nambajimana et al. 2019)

\[ C = \frac{-NDVI + 1}{2} \]  

where C is the resistance of cover management to soil erosion and NDVI is the Vegetation Index.

2.3.5. Land management (P)

This factor reflects the ratio of soil loss under good support practice to the soil loss with tilling up and downslope (Wischmeier and Smith 1978; Renard et al. 1996). Thus; reflects the impact of different soil conservation practices to prevent soil erosion (Kidane et al. 2019; Phinzi and Ngetar 2019). The dimensionless P-factor typically ranges between 0 and 1 with higher values denoting inexistence soil erosion control, while the values decrease to near zero according to the support practices applied in a region (Prasannakumar et al. 2012). It can be noted that a well-established conservation measure is a key input to reduce significantly the average erosion rate (Özşahin and Eroğlu 2019). Unfortunately, the entire province is still unsustainably and inappropriately treated in terms of soil and water conservation measures (Ocimati et al. 2020). As a result, small farmers continuously practice intensive tillage on steep and downslope land without resistant erosion control measures, which fact has made previous studies in the region and the country assume value 1 to the P-
factor (Kulimushi 2016; Kabantu et al. 2018) denoting quasi-inexistence of erosion control techniques. In such a poor land management scenario 0.75 was assigned to P factor following the Land Degradation Assessment in Drylands (LADA) project (Karamage et al. 2016).

In remedy to the above as illustrated in Table 3, the present study also assessed the influence of terracing, strip-cropping, and contouring the most commonly used and well-known support practices (Stone and Hilborn 2012) applied worldwide in agricultural land to mitigate and counter the soil erosion (Panagos et al. 2015). It is worth evaluating their impact to identify the best conservation technique to recommend, which potentially mitigate or decrease the average rate of soil erosion (Bazzoffi and Gardin 2011).

3. Results

3.1. Development of RUSLE factors database

3.1.1. Erosivity factor (R)

The erosivity factor was calculated at grid-scale based on good time-series average monthly precipitation of the past 25 years (1995–2019) derived from the historical high-resolution satellite imagery (0.05°) provided by the Climate Hazards Group InfraRed Precipitation (CHIRPS) (Funk et al. 2015). The long-term means annual rainfall was subjected to geostatistical interpolation using inverse distance weight (IDW) to obtain the raster continuous grids (Wijesundara et al. 2018; Panditharathne et al. 2019).

The current study has been constrained to use such a dataset by lack of rain-gauged station data surrounding the province. Additionally, CHIRPS rainfall data was recommended for its accuracy, good correlation with in-situ data, and their reliability in the quantitative evaluation of soil erosion by water (Dinku 2016; Fenta et al., 2017). The calculated long-term annual rainfall ranged from 872 to 2631.59 mm/y denoted the average and standard deviation of 1857.19 and 405.2 mm/y respectively. Using equation (2), as given in Figure 3(a), the erosivity factor range from 3074.67 to 9196.41 MJ mm ha⁻¹ h⁻¹ yr⁻¹, from low to high respectively. Resulting in average and standard deviation of 6501.5 and 1301.37 MJ mm ha⁻¹ h⁻¹ yr⁻¹ respectively.

The results revealed that South-Kivu is a highly erosive province, three times higher than the global average of 2000 MJ mm ha⁻¹ h⁻¹ yr⁻¹ reported by Borrelli et al. (2017). The erosivity is not uniformly distributed, it increases gradually from eastern to center, west, and north, such variation can indicate the estimated soil

| Slope (%) | Contouring | Strip-cropping | Terracing |
|----------|------------|----------------|-----------|
| 0–7.0    | 0.55       | 0.27           | 0.1       |
| 7–11.3   | 0.6        | 0.3            | 0.12      |
| 11.3–17.6| 0.8        | 0.4            | 0.16      |
| 17.6–26.8| 0.9        | 0.45           | 0.18      |
| >26.8    | 1          | 0.5            | 0.2       |
erosion (Kidane et al. 2019) despite the observed erosivity variation within the province, it can be noted that all parts had contributed significantly to the total soil loss since the erosion by water depends at 80% on the erosivity values (Renard and Freimund 1994; Meusburger et al. 2012) which were found very higher in the entire province.

3.1.2. Erodibility factor (K)
The study estimated K-factor values-based on two relevant soil properties (topsoil texture and organic carbon) extracted from the Africa Soil Information Service (AfSIS) database (Hengl et al. 2015). The final computation showed that K-factor values were found in the range of 0.0009 to 0.05 tons ha h ha\(^{-1}\) MJ\(^{-1}\) mm\(^{-1}\) with a mean of 0.028 tons ha h ha\(^{-1}\) MJ\(^{-1}\) mm\(^{-1}\) (Figure 3(b)). The obtained K factor in vector format was interpolated to generate a continuous raster grid using Inverse Distance Weight in ArcGIS software.

As stated by FAO (2001) cambisols are responsible for the high occurrence of soil erosion in tropical and subtropical areas while the cambisols are among the dominant soils group in the province share about 30% of the total province area. It can be concluded that erosion by water might be expected due to the fragility and poor drainage capacity, and high susceptibility of cambisols to soil erosion.

3.1.3. Slope length and slope steepness factors (LS)
The marginal topography that characterized the South-Kivu provides insight into the resulting LS factor values. The low elevation <1000 masl including low to moderate slope found toward western indicate the low to moderate susceptibility, while the high elevation and steep slopes observed throughout the other parts of the study area denote the potential land susceptibility to moderate and extreme risk of soil erosion.

South-Kivu topography is characterized by an average slope of 9.82\(^\circ\) and ranged from 0 to 74\(^\circ\), it has been found that more than 37.3% of the province area has slope values above 10\(^\circ\). The calculated average slope steepness (S-factor) was 2.2, values range from 0.03 to 15.7, and the average slope length of 2.10 indicating shortness and the steepness of the slope. The final LS-factor resulted from the multiplication of L and S separated showed an average of 5.92 (Figure 3(c)) while the LS values are mostly concentrated between 1 and 10, occupied 60% of the total surface erosive area, the values higher than 10 are distributed on 21% of the total study erosive area.

3.1.4. Cover management (C)
The analysis revealed that C-factor ranges from 0.04 to 0.47 resulting in a mean of 0.15. The zonal statistic tool of ArcGIS software used to perform the statistical analysis has revealed that about 45.16% of the entire province has values above the mean. The spatial distribution also revealed that values are decreasing toward the western displayed in Figure 3(d), more vegetation observed in that region predicts low to moderate soil erosion potential, because the biomass layer dissipates the raindrops energy before it impacts the soil surface (Pimentel et al. 2005) and maintains the cohesiveness of the topsoil surface. While the higher values i.e., least covered are mostly found toward east, northeast, and southeast, reflecting the vulnerability and
susceptibility of the area to soil erosion. Since, the loss of vegetation or loss of bio-
mass exposes the topsoil to the effect of high rainfall intensity observed in the entire
province, and further, accelerating the rill and gully erosion (Lal 1994).

3.1.5. Land management (P)
The present research allocated P-factor values of 0.75 assuming that although support
practices are not appropriated, smallholder farmers attempt unsustainable traditional
methods (Ocimati et al. 2020). The no adoption of sustainable erosion control meas-
ures at the regional level is not current. This problem was alarmed earlier by
Rishirumuhirwa (1994) who stated that ‘farmers can either aggravate erosion damage
with inefficient methods of soil management or reduce it by appropriate control tech-
niques’. Since then, the problem is still persistent in the DRC in general and the
study region in particular. In South-Kivu, smallholder farmers are characterized by
their land tenure, small size, rudimentary farming system, the subsistence of agricul-
ture, and poverty which facts made it difficult for farmers to adopt sustainable soil
conservation practices (Heri-Kazi and Bielders 2020). Furthermore, the political
instability observed during the past two decades in the country, witnessed by lack of
government plans, projects, and policies which in turn might enforce the adoption of
erosion control measures, on the contrary, has contributed a lot to the current situ-
uation (Kabantu et al. 2018).

Figure 4. (a) Potential soil erosion rate in South Kivu with respect to natural factors (R, K, and Ls);
(b) Estimation of soil loss rate in South Kivu considering all RUSLE factors. Source: Author.
3.2. Potential soil erosion risk

South-Kivu is naturally susceptible, vulnerable, and potentially prone to extreme soil erosion by runoff, attributed to its natural characteristics and biophysics factors in terms of high erosivity, fragile soils, and marginal topographic features. The estimated soil erosion rate of 1115.63 t ha\(^{-1}\)yr\(^{-1}\) resulting in total soil loss estimated at 16.8 million tons triggered by the above natural factors confirmed that statement (Figure 4(a) and Table 4).

It can be observed from Figure 4(a) and Table 4 that, high, very high, and extremely high soil erosion hotspots are predominant in the entire province, cover about 90.8% of the total province erosive land, and contribute by themselves 99.5% to the total soil loss per annum, from which extremely high severity class >300 t ha\(^{-1}\)yr\(^{-1}\), with highest mean of 1493.72 t ha\(^{-1}\)yr\(^{-1}\), covers 71.9% and contribute to the total annual soil loss by 96.2%.

3.3. Actual soil erosion

The soil erosion map modeled using RUSLE (R \times K \times LS \times C \times P) revealed that South-Kivu undergone an average erosion rate estimated at 138.2 t ha\(^{-1}\)yr\(^{-1}\) resulting in the total annual soil loss of 2.08 million tons (Figure 4(b)). Based on the classification adopted, it has been found that 54.74% of the South- Kivu’s erosive area experienced moderate erosion rate ranged from 0–100 t ha\(^{-1}\)yr\(^{-1}\) with annual soil rate and deviation of 37.24 and 28.01 t ha\(^{-1}\)yr\(^{-1}\) respectively, this class was responsible for 14.74% of the total predicted soil loss per year (Table 5).

High erosion severity class ranged from 100–200 t ha\(^{-1}\)yr\(^{-1}\) was observed on 20.6% spatial share of the total erosive land with a mean and standard deviation of 145.35 and 28.44 t ha\(^{-1}\)yr\(^{-1}\) respectively. Further, it contributes 21.72% to the total annual soil loss. Moreover, the very high severity class which ranged from 200 to 300 t ha\(^{-1}\)yr\(^{-1}\), comprised 11.34% of spatial distribution over the entire province, further it averaged annually erosion rate and a standard deviation of 243.50 and 28.41 t ha\(^{-1}\)yr\(^{-1}\) respectively, and consequently added 19.97% as a contribution to the predicted total soil loss. Finally, the extremely high severity above >300 t ha\(^{-1}\)yr\(^{-1}\), was spatially distributed on 13.23% with a mean and deviation of 455.04 and 195.74 t ha\(^{-1}\)yr\(^{-1}\), consequently, this class is responsible for 43.55% of the total soil loss per annum (Table 5). The average found which was nearly fourteen times greater than the tolerable rate 10 t ha\(^{-1}\)yr\(^{-1}\), incite the immediate need to look at sustainable conservation measures for better conservation of water and soil resources while keeping safe the environment.

| Severity classes | Range (t ha\(^{-1}\)yr\(^{-1}\)) | Area % | Area ha | MSL (t ha\(^{-1}\)yr\(^{-1}\)) | STD | TSL (t) | TSL (%) |
|------------------|---------------------------------|-------|--------|-----------------------------|-----|--------|-------|
| Moderate         | 0–100                           | 9.16  | 528119.28 | 57.18                       | 25.52 | 78907.28 | 0.47  |
| High             | 100–200                         | 10.58 | 610398.74 | 148.31                      | 28.66 | 236551.68 | 1.41  |
| Very high        | 200–300                         | 8.36  | 482195.87 | 247.21                      | 28.47 | 311484.65 | 1.85  |
| Extremely high   | >300                            | 71.90 | 4147649.84 | 1493.73                    | 3142.84 | 16189017.31 | 96.27 |
| South Kivu       | 100                             | 1115.63 | 1290 | 16815960.92 | 100  |

MSL: Mean soil loss, STD: Standard deviation, TSL: Total soil loss
3.4. Estimation of soil loss at the territory level

The overall territories were studied separately to discover the variation of soil erosion rate along with the territory’s contribution to the total predicted soil erosion in South-Kivu (Table 6). The results revealed that soil erosion worsening nearly the whole territory. Apart from that, the variability among territories was also observed, which was found in the range of 87.6 and 248.41 t ha\(^{-1}\) \(\text{yr}^{-1}\), as it can be seen, the range of soil erosion rate within territories still beyond the tolerable rate, thus denoting a critical need for urgent soil control measure in the province.

The soil erosion with a very high-risk range (200–300 t ha\(^{-1}\) \(\text{yr}^{-1}\)) was found in Uvira and Walungu averaged the soil erosion rate of 248.41 and 238.17 t ha\(^{-1}\) \(\text{yr}^{-1}\) respectively. High erosion might be attributed to their mean slope of 23.7% and 24.12% respectively. Moreover, these territories contributed 10.27% and 4.98% of the total soil loss, while they share in the same order 5.72% and 2.89% of the total South-Kivu land. While the high soil erosion risk range (100–200 t ha\(^{-1}\) \(\text{yr}^{-1}\)) was found in five territories such Kalehe, Mwenga, Kabare, Fizi, and Idjwi, and the city of Bukavu whose entities occupied nearly half of the South-Kivu area (48.5%) and consequently responsible for 57.6% of the predicted annual soil erosion. The study revealed that only Shabunda accounts for 42.8% of the South-Kivu’s erosive land, suffering from moderate erosion risk, respectively 87.6 t ha\(^{-1}\) \(\text{yr}^{-1}\) but, the territory added 27.14% as a contribution to the total South-Kivu erosion hazard. Despite the higher average rainfall of 2131.5 mm/y, the territory had a gentle mean slope of 13% and it’s highly covered by closed forest.

Although Shabunda experienced the lowest erosion rate compared to other territories, the soil erosion was greater than the tolerable rate set to 10 t ha\(^{-1}\) \(\text{yr}^{-1}\) indicating the need for sustainable planning to protect the natural resources. Planners should focus mainly on very high and high soil erosion hotspot territories.

3.5. Soil erosion rate and LULC categories

The spatial variation of soil erosion rate in different LULC categories revealed high soil erosion in Perennial crops, trees, and agricultural lands respectively (241.1 t ha\(^{-1}\) \(\text{yr}^{-1}\), 183.1 t ha\(^{-1}\) \(\text{yr}^{-1}\), and 161.1 t ha\(^{-1}\) \(\text{yr}^{-1}\)), in comparison to forest and shrub recorded an average rate of 127.8 and 111.6 t ha\(^{-1}\) \(\text{yr}^{-1}\) respectively. The high soil loss rate observed in the perennial crops, trees, and cropland were mainly due to their high mean slope of 25.93%, 22%, and 19% respectively. In contrast to the low topography observed in the forest with a mean slope of (17%) and shrub (17%) (Figure 5).
However, the forest and cropland were land cover categories to contribute a lot to the total soil loss in the province. In the same order, they were responsible for 59.3% and 24.4% of the total soil loss. The closed forest is the major land cover that comprises 64.2% of total erosive land followed by the cropland which shares 20.9%. This highest contribution of these LULC categories is mainly due to the larger area coverage (Gashaw et al. 2019), while, the high susceptibility of unprotected agricultural land might explain its higher contribution (Fu et al. 2006).

**3.6. Soil erosion rate and slope gradient**

The soil erosion map was overlaid with the slope map to understand how the soil erosion was varied in different slope classes along with their contribution. Following Karamage et al. (2016), four slope classes were generated and then enumerated. The spatial distribution revealed an increase in mean soil erosion rate with the increase of slope angle. The range found between 56.32.9 t ha\(^{-1}\) yr\(^{-1}\) in very gentle or flat and 243.70 t ha\(^{-1}\) yr\(^{-1}\) in very steep, still beyond the tolerable erosion rate (Figure 6).

Therefore, despite the flatness or very gentleness of the slope, there is a need for erosion control measures at each slope angle level. A very steep slope recorded a very high average soil erosion rate of 243.7 t ha\(^{-1}\) yr\(^{-1}\) shared 17.8% of South-Kivu erosive

| Territories | Area (%) | Area (ha) | MSL (t ha\(^{-1}\) yr\(^{-1}\)) | TSL (ton yr\(^{-1}\)) | TSL % | Mean Slope (%) |
|-------------|----------|-----------|-------------------------------|----------------------|-------|----------------|
| Uvira       | 5.72     | 330058.38 | 248.41                        | 214162.36            | 10.27 | 23.72          |
| Walungu     | 2.89     | 166943.68 | 238.17                        | 103859.65            | 4.98  | 24.12          |
| Kalehe      | 7.16     | 412764.43 | 194.13                        | 209300.52            | 10.04 | 24.32          |
| Mwenga      | 19.60    | 1130698.84| 176.57                        | 521483.26            | 25.02 | 20.36          |
| Kabare      | 3.58     | 206765.11 | 173.75                        | 93841.13             | 4.50  | 20.20          |
| Bukavu      | 0.05     | 3063.19   | 140.82                        | 1126.72              | 0.05  | 23.97          |
| Fizi        | 17.74    | 1023104.41| 137.34                        | 367016.09            | 17.61 | 19.38          |
| Idjwi       | 0.38     | 21825.21  | 136.04                        | 7755.25              | 0.37  | 20.98          |
| Shabunda    | 42.87    | 2473140.48| 87.61                         | 565933.57            | 27.15 | 13.08          |
| South Kivu  | 100      | 5768363.72| 138.29                        | 2084478.53           | 100   | 17.73          |

MSL: Mean soil loss, TSL: Total soil loss

Figure 5. Mean soil loss, total soil loss, area, and slope in erosive LULC categories.
lands, it was responsible for 31.3% of the total soil loss. The highest share of the total soil loss was found in the steep angle class (36% of share), averaged annually 164.7 t ha\(^{-1}\) yr\(^{-1}\) of soil loss, and occupied 30.3% of South-Kivu’s erosive land.

4. Discussion

4.1. Soil erosion risk in South-Kivu

South-Kivu is a highly erosive province following its high mean erosivity factor with a mean of 6501.5 MJ mm ha\(^{-1}\) h\(^{-1}\) yr\(^{-1}\). The analysis revealed marginal topography with an average LS factor of 5.5, fragile haplic acrisols, and humic cambisols the most dominant soil groups with an average K factor of 0.028, resulting in high fluctuation of potential erosion risk rate estimated at 1115.63 t ha\(^{-1}\) yr\(^{-1}\). In reverse, South-Kivu is still densely covered 64.3% resulting in a low C factor value with a mean of 0.15. The actual soil erosion risk estimated at 138.29 t ha\(^{-1}\) yr\(^{-1}\) that is less than the potential soil loss was reported by Wischmeier and Smith (1978) and Karamage et al. (2016) which denotes the greatest vulnerability and highest fragility of the study area to soil erosion.

The findings are correlated with high hazards prediction in sub-Saharan Africa, where natural and man-induced factors lead to the degradation of the natural environment, thus initiating the change occurred of many natural geo-hazards, including the soil erosion (Borelli et al. 2013). In the same line, the result is in agreement with the previous study carried at plot scale in Kabare territory, in which the study estimated the average erosion rate of 450 t ha\(^{-1}\) yr\(^{-1}\) (Heri-Kazi and Bielders 2018).

The variation of soil loss rate at the territory level found between 87.6 t ha\(^{-1}\) yr\(^{-1}\) in Shabunda and 248.41 t ha\(^{-1}\) yr\(^{-1}\) in Uvira highland, match with previous reports in great lake regions. For instance, Karamage et al. (2016) reported the soil erosion rate of 250 t ha\(^{-1}\) yr\(^{-1}\) for the whole of Rwanda (ranging from 94 to 678 t ha\(^{-1}\) yr\(^{-1}\)), and consistent with soil erosion rate ranging from 37 to 322 t ha\(^{-1}\) yr\(^{-1}\) for Burundi, where very severe erosion rate shared more than 64% of total Burundi’s land area (Nijimbere and Lizana 2019), and comparable to the range of 80 and 150 t ha\(^{-1}\) yr\(^{-1}\), estimated from Mumirwa mountainous in Burundi (Mathieu 1987), the similar average was estimated in Mount Elgon region in Uganda (Jiang et al. 2014). The same results were found in African countries having similar geo-environmental conditions,
absence of sustainable erosion control, and where human intervention has been men-
tioned to be among the major factors accelerate the pressure to natural ecosystem
thus increase the soil erosion risk. For instance, in Jijel Wilaya, Algeria, the soil loss
rate of 286.4 t ha\(^{-1}\) yr\(^{-1}\) was reported by Nehai and Guettouche (2020), and many
authors argue with these findings including (Payet et al. 2012; Toumi et al. 2013;
Rushema et al. 2020).

Assuming that the soil erosion depends at 80% on the erosivity values as literature
reports (Renard and Freimund 1994; Meusburger et al. 2012), typically South-Kivu
should have undergone extreme erosion risk compared to the above countries, while
the estimated soil erosion risk is relatively similar. However, the long-term mean
rainfall of the present study 1857.19 mm/year, is by far greater than the average
annual precipitation of the previous countries, in reverse, the soil erosion in South-
Kivu should be relatively higher than in those countries. Nevertheless, invariable
results were found, such as the overall highest mean rainfall intensity of
2125.046 mm/year has been observed in Shabunda but the soil loss rate was moder-
ated (87.6 t ha\(^{-1}\) yr\(^{-1}\)). It means the variation of soil erosion in South-Kivu is not sig-
nificantly affected by the increase of rainfall intensity.

In the line of the results found, the study agreed with Lal (1994) stated that, des-
pite high rainfall, the biomass found in undisturbed and densely covered area dissi-
pate the kinetic energy of raindrops hence decrease the aggressiveness of rainfall to
the surface (Pimentel et al. 2005). The study also agreed with Alkharabshheh et al.
(2013) who pointed out the important role play by topographic features in aggravat-
ing or alleviating the runoff energy resulting in a considerable variation of soil ero-
sion as well (Phinzi and Ngetar 2019). Therefore, cover management and
topographic features were the most important RUSLE parameters driving the pre-
dicted severity of soil erosion under high rainfall aggressiveness conditions charac-
terize the South-Kivu. As stated by Pimentel and Burgess (2013) erosion is intense
in the least vegetative cover, with erosion rates that are estimated around 75 times
greater than erosion in well-covered natural forest. In Jamaica, the slope greater
than 20% occupied 52% of the total land, was reported to be responsible for unsus-
tainable soil erosion rates higher than 400 t ha\(^{-1}\) yr\(^{-1}\) (Lal and Stewart 1990).

For instance, the considerable proportion of perennial crop, trees, and cropland
added to the high mean slope ranging from 20% to 24% observed in Uvira, Walungu,
Kalehe, Mwenga, and Kabare regardless of the mean rainfall intensity of 1686.5 mm/
year; low C and high LS factors values increased the vulnerability of the aforesaid ter-
ritories to soil loss.

In these territories like others, the erosion hazard is accentuated by a lack of soil
erosion control; as a result, contributed significantly to accelerate runoff downslope.
Consequently, droving high to extreme soil erosion which in turn, accelerates the
land degradation and soil nutrient deprivation (Lunze 2000), a decline in agricultural
yield (Muhindo 2015) finally, lead to food insecurity in the province at a proportion
of 60% (Walangululu et al. 2010). Hence, conservation appears to be the most
important factor to reduce the rate of runoff and prevent soil erosion under steep
cultivated areas (Panagos et al. 2015; Thomas et al. 2018).
4.2. Role of conservation measures to prevent soil erosion in South-Kivu

In line with the above, it was important to discuss the role play by diverse support practices to prevent soil erosion in South-Kivu. Considering the agricultural land including both (cropland and perennial crop) which in 2018, account for 21.1% of the total South-Kivu erosive land, overlapped with slope gradient, a comparison of the most known conservation techniques was carried out and denoted a significant variation of the mean soil erosion rate (Figures 7 and 8).

Terracing was the most suitable conservation technique that should be implemented in South-Kivu. As it is given in Figures 7(b) and 8(b), the adoption of terrace could reduce by approximately 76% the current rate observed in cropland; i.e., from 162.12 t ha\(^{-1}\) yr\(^{-1}\) to 38 t ha\(^{-1}\) yr\(^{-1}\) further, the moderate erosion class <100 t ha\(^{-1}\) yr\(^{-1}\) could contribute by around 60% of the total soil loss compared to the current contribution of about 10% in agricultural land (Figures 7(a) and 8(a)).

The second support practice is strip-cropping, the result revealed that by adopting strip-cropping, the soil erosion rate could be reduced by only 41%, resulting in a mean soil loss of 95.47 t ha\(^{-1}\) yr\(^{-1}\) as compared to the current rate in cropland of 162.12 t ha\(^{-1}\) yr\(^{-1}\). Moreover, the contribution of moderate soil erosion could decrease in turn increase the severity of extreme erosion (Figures 7(c) and 8(c)). Planners should avoid the use of contour farming as a support practice, this technique instead of improving the current rate, in reverse had aggravated it (Figures 7(d) and 8(d)). The use of contour farming could increase by 18% compared to the current rate in cropland; from 162.12 t ha\(^{-1}\) yr\(^{-1}\) to 191.14 t ha\(^{-1}\) yr\(^{-1}\). Moreover, extreme soil erosion class could

Figure 7. Area in % and total soil loss in % under diverse support practices. (A) The current status in cropland, (B) Terracing, (C) Strip-cropping and (D) Contouring.
contribute to about 80% of the total soil loss in cropland. Hence, it is not recommended. It has been also noticed recently in Rwanda, contouring exacerbated the soil erosion rate by four times compared to the estimated soil loss (Nambajimana et al. 2019) and in Uganda, contouring was not recommended because there was no change in soil loss rate under application of contouring as support practice (Karamage et al. 2016). In contrast to terracing as a good alternative of soil erosion control, has demonstrated its capability in the landscape to significantly mitigate the soil erosion, and reduce the hillslope gradient (Nyssen et al. 2007; Bazzoffi and Gardin 2011; Stanchi et al. 2012; Panagos et al. 2015).

5. Conclusion and recommendations

GIS and remote sensing technology using the global open dataset is a powerful tool to model the soil erosion hazard especially in poor data context as the current, where the soil erosion map longs for the colonial epoch. The overall average soil erosion rate in
South-Kivu was estimated at 137 t ha\(^{-1}\) yr\(^{-1}\), which was nearly fourteen times greater than the tolerable rate of 10 t ha\(^{-1}\) yr\(^{-1}\). The soil erosion worsening nearly the entire territories range from 87 t ha\(^{-1}\) yr\(^{-1}\) in Shabunda to 248 t ha\(^{-1}\) yr\(^{-1}\) in Uvira. Erosion hazard at territory level increased in descending order of Uvira, Walungu, Kalehe, Mwenga, Kabare, City of Bukavu, Fizi, Idjwi, and Shabunda. Cover management and topographic features were the most important RUSLE parameters driving the predicted soil erosion under high rainfall aggressiveness characteristics of the South-Kivu. Perennial crop, trees, and cropland with a mean slope of 25.9%, 22%, and 19% respectively, were the most vulnerable LULC categories. In contrast to the shrub and forest recorded the lower rate of soil loss (111.6 t ha\(^{-1}\) yr\(^{-1}\) and 127.8 t ha\(^{-1}\) yr\(^{-1}\)) located both at 17% of the mean slope. The study revealed that the adoption of terracing could reduce by 76% the soil erosion in cropland, then strip-cropping (41%) and contouring which in reverse, could exacerbate by 18% the soil erosion in cropland.

GIS and remote sensing-based RUSLE model have demonstrated to be a suitable approach for soil mapping and estimation of soil erosion, especially in the poor data context. The valuable outcomes from this study kept policymakers and managers aware of the reliably predicted erosion phenomena within the province, it can help to manage land and water resources by adopting terraces to reduce the slope length hence minimize soil erosion below the current rate. Finally, future research could contribute to link soil erosion to the socio-economic problem.

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Data availability statement

The data that support the findings of this study are openly available in figshare at https://doi.org/10.6084/m9.figshare.13513686.v1

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