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Modelling soil erosion risk in rural sub-catchments of Zimbabwe using RUSLE, remote sensing and machine learning

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ABSTRACT

The study modelled soil erosion risk in the Shashe and Tugwi–Zibagwe rural sub-catchments in Zimbabwe. To derive land use and land cover (LULC) thematic maps for the years 2016, 2020 and 2023, analysis ready data (Sentinel 2) were applied using the Random Forest (RF) algorithm in the Google Earth Engine (GEE) platform. The Revised Universal Soil Loss Equation (RUSLE) model was applied to understand the drivers of soil loss in the sub-catchments. The rainfall erosivity (R), soil erodibility (K), length slope (LS), crop management (C) and conservation support practice factors (P) were derived in GEE and applied as input to determine soil erosion risk. The findings of the study show that, the Shashe sub-catchment had mean soil losses of 15.75, 45.25, and 23.51 t ha^{-1} year^{-1} for 2016, 2020, and 2023, respectively. In the Tugwi-Zibagwe sub-catchment, the mean soil losses were 11.62, 18.45, and 37.34 t ha^{-1} year^{-1} for the same years. The results also show that LULC changes were one of the major drivers to soil loss in the rural dominated sub-catchments. Results further show that, the area under cultivation was exposed to severe erosion which averaged 16–48 t ha^{-1} year^{-1} when compared to other land covers in the study areas. In conclusion, of all the two sub-catchments the Shashe experiences severe soil loss than Tugwi-Zibagwe due to variations in land use and covers. Soil loss also tends to be considerably high in areas along drainage networks and where vegetation clearance is evident. These findings highlight the pressing need for up-to-date soil management approaches to improve soil conservation in rural dominated sub-catchments of Zimbabwe.

1. Introduction

Soil erosion cannot be regarded as a new issue since of late it has been regarded as a serious environmental hazard (Poesen, 2018; Phinzi et al., 2021; Musasa et al., 2024). Land degradation is singled out as a significant environmental concern worldwide, predominantly in areas that depend on agricultural activities (Abdulkareem et al., 2019; Senanayake et al., 2024), with 85 % of this degradation attributed to soil erosion, a pervasive issue across the globe (Senanayake et al., 2024). LULC change which is the main driving factor, affects soil quality and sub-catchments hydrology (Paul et al., 2019; Cui et al., 2022; Senanayake et al., 2024). Therefore, it is imperative to evaluate LULC alterations and its related impact on soil loss.

Worldwide, soil erosion occurrence is a common phenomenon in communal agricultural areas and is estimated to be between 25 and 90 t ha^{-1} year^{-1} causing a decrease of 15–30 % in terms of productivity (Getu et al., 2022). Of late, the growing demand for crop cultivation in developing countries has led to extensive land clearance, causing significant degradation (Li et al., 2023; Senanayake et al., 2024). Despite this concern, detailed information on the influence of LULC changes on the rate of erosion and fertility depletion at local scales, such as district and sub-catchment levels, remains scarce. This lack of data raises concerns about the effectiveness of strategies aimed at promoting sustainable environmental management. Literature reveals that accurate detection of LULC change is often challenging due to massive land use fragmentation (Paul et al., 2019; Senanayake et al., 2024). This challenge has prompted broader exploration, with remote sensing (RS) emerging as a promising solution.

Despite being highly accurate, traditional field-based methods applied for LULC change detection and soil erosion monitoring and assessment in sub-catchments, have proven to be expensive (Phinzi et al., 2021), labour-intensive, time-consuming and difficult to carry out,

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especially over large and inaccessible areas (Seutloali et al., 2017; Alebachew et al., 2025). With the advancements and progress in remote sensing, earth observation and geospatial methods have proven to offer more practical and cost-effective means to predict and quantify soil erosion risk, intensity and its occurrence both locally and globally. From a global point of view, several studies have been conducted to understand the spatial distribution and occurrence of soil erosion in varying environments (Paul et al., 2019; Obiahu and Elias, 2020).

In Southern Africa, few studies (Sepuru and Dube, 2018; Marondedze and Schütt, 2020; Dzawanda and Ncube, 2022) have utilized spatial techniques to assess soil erosion occurrence in sub-catchments. For instance, Seutloali et al. (2017), utilized topographic and rainfall variables to assess key drivers and mapped the distribution of erosion in the former South African homelands of Transkei. However, the major challenge is that some of the studies conducted adopted high-resolution remotely sensed data from QuickBird and WorldView, to map eroded surfaces (Phinzi et al., 2021). Moreover, the application of OBC to Landsat (medium resolution) and other readily available data such as Sentinel 2 MSI has not yet been reconnoitred although it has prospects for effective solution as it can provide an inventory of global data coverage which has enhanced soil erosion assessment and monitoring (Paul et al., 2019). This implies that if the quality of assessments in environmental monitoring is to be improved focus should also be placed on need to understand the magnitude of erosion influenced by LULC change. Studies conducted in Zimbabwe, for example, Dzawanda and Ncube (2022), mainly focused on the vegetation changes and soil erosion hazard using single point data to assess the spatial and temporal occurrence of erosion which the present study seeks to improve by using multi-date remotely sensed data.

To date, several models have been advanced to envisage soil erosion. This has witnessed the emergence of robust practical models such as e.g the Revised Universal Soil Loss Equation (RUSLE) which has gained acceptance in soil loss risk estimation (Wischmeier and Smith, 1978; Bagherzadeh, 2014; Alebachew et al., 2025). To add on, models like the United States Department of Agriculture-Water Erosion Prediction Project (WEPP) (Nearing et al., 1989) and European Soil Erosion Model (EUROSEM) (https://www.frontiersin.org/journals/forests-and-global-change/articles/10.3389/ffgc.2023.1124677/full) have also aided soil risk estimation. Although, numerous models have been put in place for soil erosion studies, the RUSLE has been the most applied (Dube, 2011; Abdulkareem et al., 2017; Paul et al., 2019; Li et al., 2023; Musasa et al., 2024). In its strict sense, a combined remote sensing and RUSLE have since proved to be effective since it is associated with less costs, time-saving and more accurate but its potential has not been fully explored (Abdulkareem et al., 2017; Yesuph and Dagnew, 2019; Phinzi et al., 2021).

The RUSLE potential to estimate soil loss was tested in the Canadian watersheds where LULC changes had significant impact on the amount of soil lost annually (Paul et al., 2019; Li et al., 2023). Abdulkareem et al., (2017) predicted soil erosion risks in the Lelantan river basin using the same approach and observed significant loss. Similarly, Phinzi et al. (2021) adopted the RUSLE in a RF combined approach and observed significant soil loss attributed to changes in land use and human activities. Dube (2011) adopted a similar approach to estimate soil loss in Mbire district and produced accurate results. This clearly shows that the model has been widely adopted, as it is simple with limited data requirements (Gaubi et al., 2017; Paul et al., 2019; Li et al., 2023).

Although great strides have been made to assess and monitor soil erosion, very few studies in Zimbabwe for example Kusena et al. (2022), have tried to combine the RUSLE model with machine learning approaches in a geospatial environment. All this implies that location specific soil erosion studies are still substantial in Zimbabwe to address the problem of soil erosion. Interestingly, the fusion of RUSLE and OBC methods using analysis ready data at district and sub-catchments scale is not well-documented (Dube, 2011; Paul et al., 2019). To add on, machine learning algorithms, for example, RF which are robust have enhanced the quality of assessments but have not been fully explored (Paul et al., 2019; Gxokwe et al., 2022). The study was undertaken with little relatively known but highly susceptible and fragile rural dominated sub-catchment areas, where soil erosion is the major challenge and common phenomenon, yet such studies are rare in light of the global pressing environmental challenges.

The present study includes a more comprehensive approach that combines a diverse set of variables, for soil erosion risk monitoring. The study therefore offers new insights as it presents relevant information on modelling potential soil erosion risk, by integrating high-resolution remote sensing data with machine learning classification methods and GIS-based spatial erosion modelling. The study also applies a robust method that employs multi-temporal LULC data to understand dynamic changes and their cumulative impact on soil erosion in a holistic manner that fills up gaps in literature and methods applied previously. An assessment of soil erosion in arid environments contributes information essential towards the attainment of the United Nations Sustainable Development Goals (SDGs) 1 (end poverty), 2 (zero hunger), and 14 (life below water). In order to effectively counteract the problems of soil erosion and militate its frustrating impacts in sub-catchments, the assessment and monitoring of soil erosion risk is essential. Against this backdrop, only a few research attempts have been documented to make such efforts. The study will primarily focus on the two distinct rural dominated sub-catchments which are located in varying Agro-Ecological Zones. The areas also have different slope length and type a factor which has significant contribution to potential soil loss. The primary objectives of this study are.

(1) To analyse land use and land cover (LULC) changes in Shashe and Tugwi-Zibagwe sub-catchments.
(2) To model potential soil erosion risk using RUSLE and remote sensing approaches.
(3) To assess the impact of LULC changes on soil erosion occurrence and intensity.

2. Materials and methods

2.1. Study area

The study areas were located in discrete Shashe and Tugwi –Zibagwe sub-catchments (Fig. 1). In terms of hydrology, the country been categorized into seven catchments, namely Gwayi, Save, Sanyati, Mazowe, Manyame, Runde and Mzingwane. Zimbabwe basically has 5 Agro-Ecological Zones (AEZs) determined by the amount of rainfall received and soil suitability for agriculture (Manatsa et al., 2020). The study areas are located in different hydrological sub-catchments that is Shashe (Mzingwane) and Tugwi-Zibagwe (Sanyati and Runde).

It is prudent to stipulate that, Tugwi –Zibagwe sub-catchment lies under region 3, 4 and 5a with rainfall ranging between 400 and 800 mm. The sub-catchment is largely covered by the green stone belt which generally develops weak soils. Generally, the soils in the rural dominated sub-catchments are mostly subjected to erosion as a result of human activities largely linked with massive cutting down of trees for fire wood.

The Shashe sub-catchment is typically located in AEZ 4–5b. To add on, there are also other areas which are to the north of Kezi which can be recognised as under AEZ 4 with rainfall below 650 mm being received (Ashton et al., 2001; Manatsa et al., 2020). There is also an area called Kafusi, which is located South of Kezi and is in AEZ 5a. There are also areas to the far south where there is Thuli and Shashe which constitute AEZ 5b. Generally, the Shashe sub-catchment experiences dry conditions also having poor soils than the Tugwi –Zibagwe sub-catchment, a position which motivates the present study to adopt a comparative approach in understanding the variations in soil erosion risk.

In Shashe sub-catchment, especially to the north of Kezi, land use is mainly commercial characterized by livestock production with some

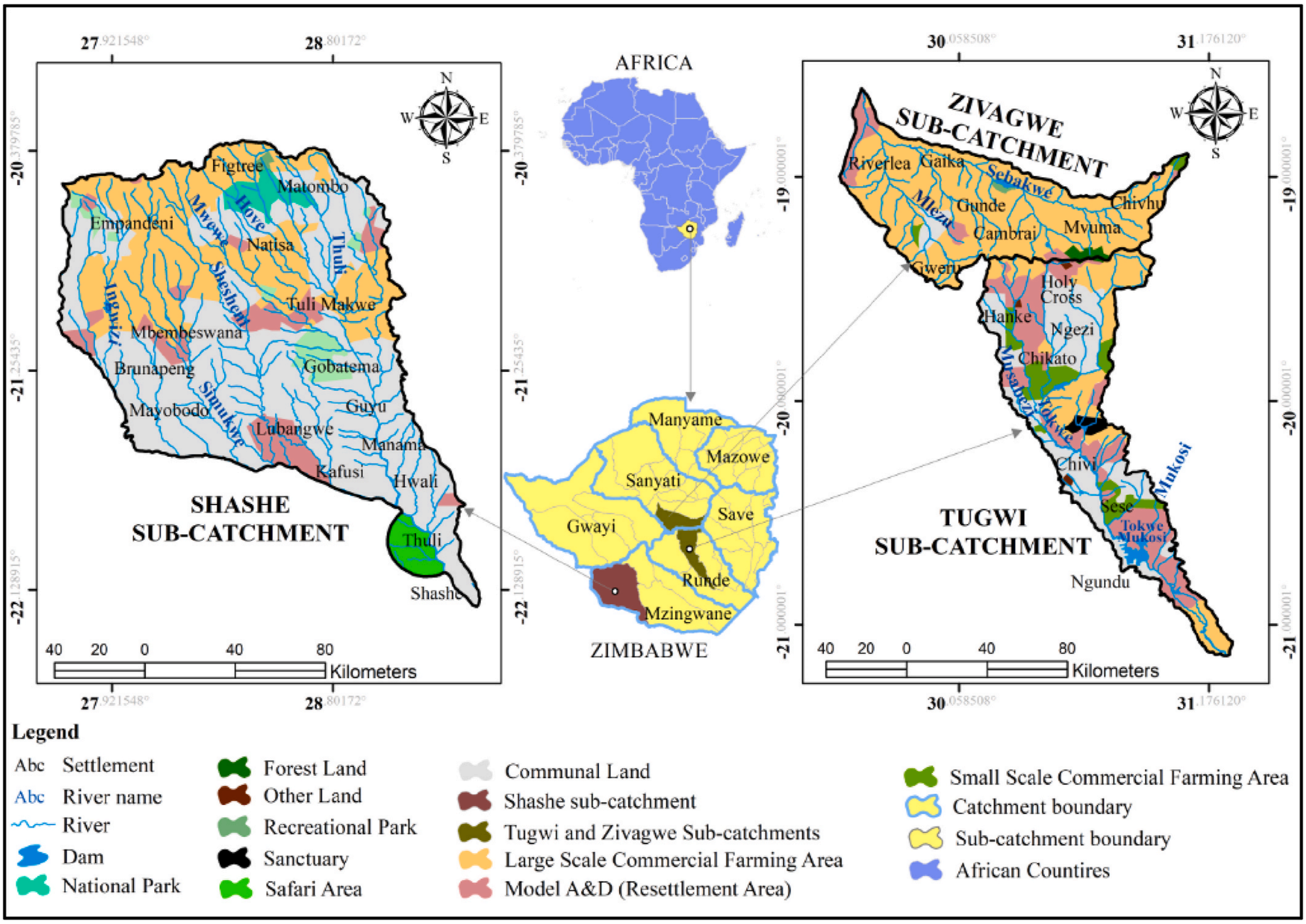

Fig. 1. Map of Shashe and Tugwi –Zibagwe sub-catchments in Zimbabwe, Source (Authors).

drought tolerant crops like sorghum and millet being grown (Fig. 1). The sub-catchment falls within the jurisdiction of Mangwe, Matobo and Gwanda Districts, with total population of and 65,562 (31,067 males and 34,495 females), 95,696 (47,124 males and 48,572 females) and 124,548 (61,600 males and 62,948 females) respectively (Zimbabwe National Statistical Agency, 2022).

In Zibagwe sub-catchment, key economic activities include mining and agriculture. The sub-catchment is within the jurisdiction of Vhungu, Kwekwe, Chirumanzu and Chikomba rural district councils. Chirumanzu, Vungu, Kwekwe and Chikomba districts which fall within this catchment have populations of 95,272 (45,589 males and 49,683 females), 121,712 (60,433 males and 61,279 females), 197,063 (98,794 males and 98,269 females) and 123,937 (59,030 males and 64,907 females) respectively (Zimbabwe National Statistical Agency, 2022). Chirumanzu District also covers part of Tugwi sub-catchment, together with Chivi, Masvingo and Shurugwi districts with total populations of 172,979 (79,556 males and 93,423 females), 238,103 (112,557 males and 125,546 females) and 98,315 (48,609 males and 49,706 females) respectively (Zimbabwe National Statistical Agency, 2022).

2.2. Field data collection

Field surveys to collect data were carried out between the January 1, 2023 and March 31, 2023 and between August 1, 2023 and October 31, 2023. In this study, a hand-held Global Position System (GPS) Garmin Etrex 30 recorded coordinates with an accuracy of 5–10 m (16–33 feet). The process of collecting data also encompassed capturing of data on major land covers, such as water bodies, cultivated + bare areas, eroded areas, grasslands and built-up areas. A total of four hundred points were picked during the process making use of GPS. Out of these samples each land cover class had 50 points which were evenly distributed and later validated using Google earth for image classification in GEE. Visual observations proved handful in selection of land cover classes with samples late being grouped.

2.3. Remote sensing data acquisition and pre-processing

In this study, the acquisition of analysis ready data was executed following the steps in Fig. 2a. Analysis ready data based on Sentinel 2 MSI Level 1C were used to assess LULC and determine RUSLE parameters such as crop management (C) and conservation practice (P) which was essential in predicting soil loss risk in the rural landscapes. The Sentinel 2 MSI level 1C (COPERNICUS/S2_SR/20161128T002653_20161128T102149_T56MNN) Surface reflectance images available in GEE were applied for the years 2016, 2020 and 2023 for the LULC classification and RUSLE parameter derivation (C factor). The data were extracted from the GEE catalogue available at https://earthengine.google.com/. These products are already atmospherically corrected by using the Sen2cor toolbox, and they contain twelve UINT16 spectral bands that are scaled by 10000, as well as three QA bands, where one (QA60) is a bitmask band with cloud mask information. Filtering of the data collected was done by the region of interest (sub-catchment scale and the date), by applying ‘Image.filterBounds ()’ and ‘ee. Filter.Date ()’. The ‘ee. Filter.eq (‘CLOUD_COVER’, 5)’ code was the applied reduce images based on cloud cover. During the processing stage of the Sentinel 2 scenes, the acquired images were first reduced

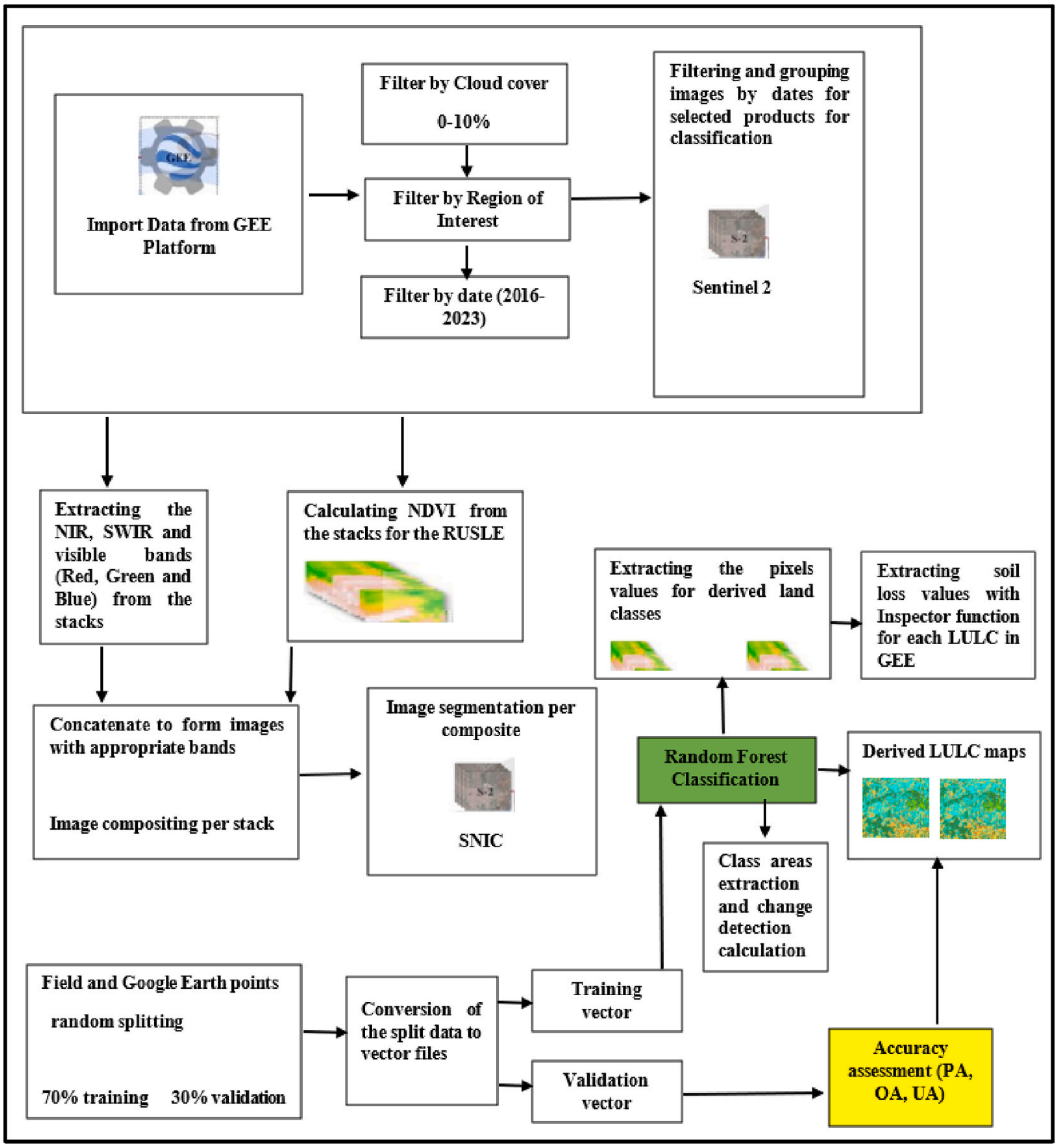

Fig. 2a. Flow chart outlining the methodology.

and normalized for the illumination and clouds effects, using the median composite algorithm, which reduces a stack of images by the computation of median values across the matching bands of a pixel in an image stack, and consequently reduces the cloud cover and illumination effects. The median composite works by reducing a stack of images through the calculation of the median of all the values at each pixel across the stack of all matching bands, thus minimising the effects of shades and clouds (Mahdianpari et al., 2019). The median composite in this study was executed by using the code "Median ()" on the GEE.

This study is quite unique in the sense that it integrates high-resolution remote sensing data with machine learning classification methods (Random Forest) and GIS-based spatial erosion modelling. This therefore, motivated the researchers to combine these robust methods which previous research has not fully explored to obtain rich information contained and harness the potential of machine learning in as far as estimation of soil erosion risk is concerned in rural sub-catchments of Zimbabwe. The study has also significance as it adopts use of multi-temporal LULC data (2016, 2020, and 2023) to understand dynamic changes and their cumulative impact on soil erosion (Table 1). Many similar studies rely on only one or two time points. Additionally, the study benefits from high-resolution spatial data, which allows for a fine-

Table 1
Number of Sentinel-2 products available after filtering by date, region of interest and cloud cover.

Remote sensing product	Year	Images obtained per month (cloud cover <5 %)		Band - spatial resolution	Tiles	
		March	October		Shashe	Tugwi-Zibagwe
Sentinel-2 MSI level 1-C	2016	5	6	3 (Green) – 10 m	T35KNS	T35KQU
	2017	6	6		T35KNT	T35KQV
	2019	4	5	&	T35KPR	T35KRT
	2020	6	6		T35KPS	T35KRU
	2021	6	6		T35KPT	T35KRV
	2022	5	6	11 (SWIR) – 20 m	T35KQR	T36KTC
	2023	5	4		T35KQS	T36KTD
					T35KQT	T36KUB

scale assessment of erosion risk across the sub-catchments of Zimbabwe.

2.4. Adopted machine learning classification scheme

The Sentinel 2 MSI level 1C was adopted for LULC classification since the data became available after 2016. In this case, the Land cover map for the RUSLE were derived from bands of Sentinel 2 MSI level 1C (bands 2 (blue), 3 (green, 10m), 4 (red, 10m), 8 (near infrared, 10m) and 11 (SWIR, 20m) (Table 1). In this study, the classification of the images was done using the Random Forest (RF) algorithm on the GEE platform. The researchers opted for this high-resolution data to enable continuity of one product so as to improve the quality of assessment. The RF algorithm is an ensemble classifier consisting of many trees where each tree casts a unit vote to split the samples. This specific algorithm was chosen, firstly, because it is capable of handling large differentiations between the landcover classes, thus neutralising the data noise, and secondly, because of its superiority to other GEE algorithms in studies, for example, Gxokwe et al. (2022).

The RF classifier was adopted due to its proven success as outlined by Saravanan and Abijith (2022), Gxokwe et al. (2022) and Laonamsai et al. (2023). In these studies, RF was among the best-performing algorithms, with a high overall and class accuracies; therefore, it was selected for this study. Prior to the classification, the collected field data were randomly split into 70 % training and 30 % validation data. The principle behind the splitting of data to 70/30 was to ensure that they represented a large training dataset, while the remaining data were preserved, in order to compute accurate statistics. After splitting, the training and validation data points were then imported and converted to shapefiles on ArcGIS, and then imported to the GEE platform, in order to train and validate the Random Forest model. The classifier was trained using the code 'ee. Classifier. Train ()' to enable it to perform its suitable operations. The classification based on RF algorithm was done using the code 'Image. Classify ()' in GEE.

2.5. Accuracy assessment

The accuracy of the derived LULC change maps for the Shashe and Tugwi –Zibagwe sub-catchments was assessed using assessment matrices namely, the User's Accuracy (UA), Overall Accuracy (OA) and the Producer's Accuracy (PA). The accuracy assessments were computed and executed in GEE to bring confidence in the quality of the maps produced. In order to achieve this, 30 % of the data which was randomly split was adopted (Fig. 2a). In this research the Kappa analysis was also performed to strengthen the numerical accuracy values. The Kappa is commonly used to determine how consistently two or more raters assign the same categories or scores to the same items which was essential in LULC change thematic maps accuracy.

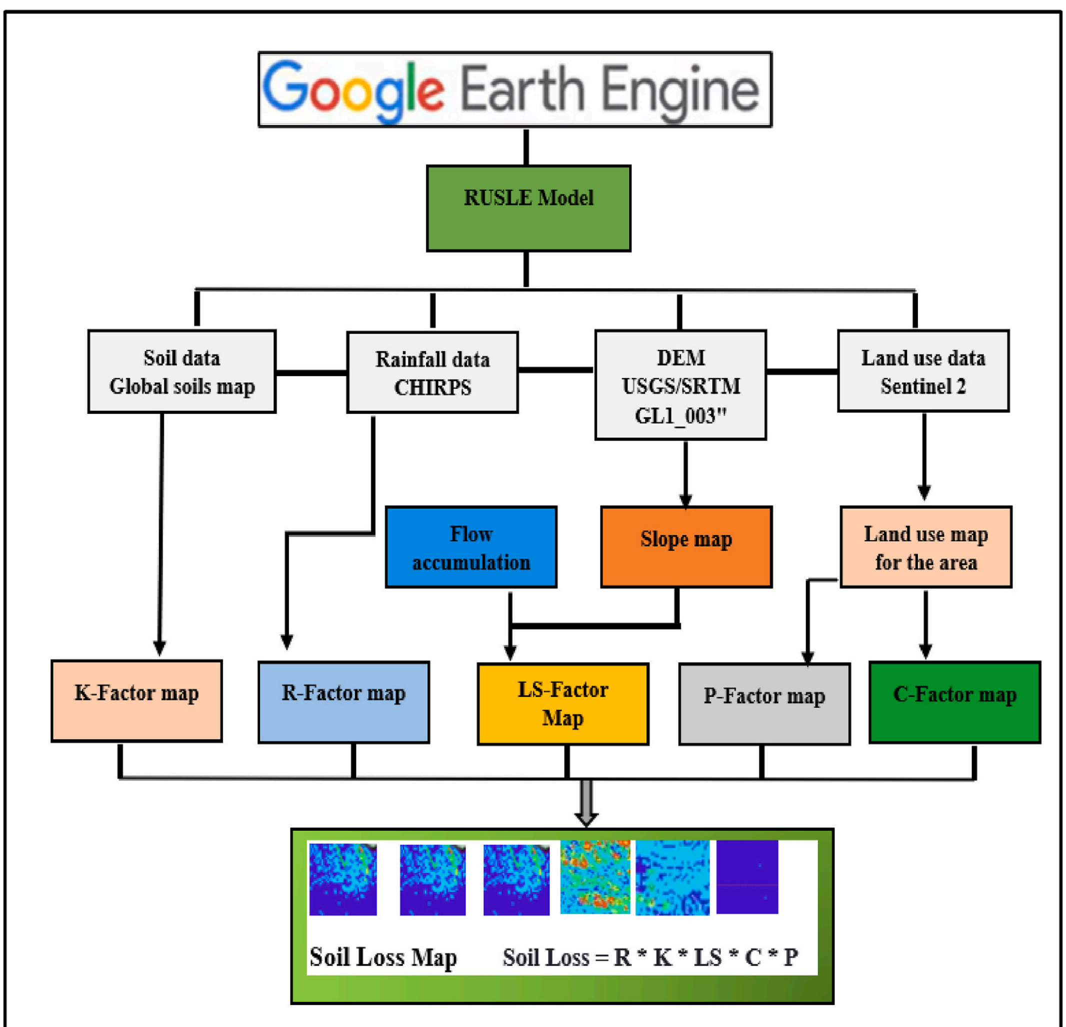

Fig. 2b. Steps taken to estimate soil loss in GEE.

2.6. Soil erosion loss estimation

RUSLE was applied to model potential soil loss under each of the identified land use types using the steps in Fig. 2b. The RUSLE has been adopted model to potential soil erosion from field level up to sub-catchment scale (Paul et al., 2019). The model was adopted as it requires less data, free hence aiding in soil loss risk estimation for resource constrained areas (Farhan and Nawaiseh, 2016). It has been represented using the following equation:

$$A = R * K * LS * C * P \tag{1}$$

where A is the annual average soil loss (t/ha/year); R is the rainfall erosivity factor (mm/ha/h/year), K -soil erodibility factor (ton/ha); LS -slope-length and slope-steepness factor, C - cover factor and P - support practice factor. The RUSLE parameters in this study were calculated using the methods illustrated in Table 2 following a detailed process as shown in the flowchart in Fig. 2b.

2.6.1. Rainfall erosivity factor (R)

R is one of the important parameters which directly depends on the strength and volumetric capacity of rainfall. The R factor refers to the potential that a rainfall has towards erosion that is usually derived by its intensity over a specific period (Wischmeier and Smith, 1978; Fenta et al., 2017). The key contributors to the R factor include rainfall intensity and duration. Raindrop or splash erosion is the primary form of erosion on exposed soil surfaces, leading to detachment and dispersion of soil particles, which are subsequently transported to downstream areas. The calculation of the R factor involves multiplying the maximum intensity of 30-min rainfall by the kinetic energy associated with individual rainfall events (Wischmeier and Smith, 1978). To obtain rainfall data for the period 2016–2023 the CHIRPS Data Service (The Climate Hazards Group Infrared Precipitation with Station Data) available in GeoTIFF was used. This format was adopted as it can be used to represent precipitation values in a raster layer. The data was accessed using the code var current = CHIRPS.filterDate(date1, date2). select ('precipitation'). sum (). clip(aoi); Map.addLayer (current, {}, 'Annual Rain', 0). The reported rainfall erosivity range of 338.57–573.37 MJ. mm. ha. hr 1. for the study area indicates significant variability in the erosive potential of rainfall events (Table 3).

Table 3
RUSLE parameter values and their sources.

Factors	Values	Source or estimation method	Reference
R	The rainfall erosivity range of 338.57–573.37 MJ. mm. ha. hr 1 was adopted.	The calculation of the R factor involves multiplying the maximum intensity of 30-min rainfall by the kinetic energy associated with individual rainfall events. To obtain rainfall data for the period 2015–2023 the CHIRPS Data Service (The Climate Hazards Group Infrared Precipitation with Station Data) available in GeoTIFF was used.	Wischmeier and Smith (1978).
K	Soil erodibility factor values ranged between 0.05 and 0.14 t ha h (ha MJ mm) −1.	The K factor is calculated in GEE using the method outlined in Table 2 having obtained data from global soils map.	Wischmeier and Smith (1978).
LS	The result of the slope length steepness factor (LS) ranging from 1.7 to 4848.8 suggests a wide variation in terrain characteristics within the study area.	The LS factor was calculated from the 30-m resolution DEM (Digital Elevation Model) and generated using SRTM in GEE.	Renard (1997)
C	Incorporated within the RUSLE formula, the C factor varies from 0.001 for dense forests to 1.0 for bare land	The C factor was derived for the study area by creating a mosaic of NDVI (Normalized Difference Vegetation Index) based on Sentinel-2 satellite imagery on the GEE platform	Renard (1997)
P	0.39 for agricultural lands and 1.0 for non-agricultural land (others)	Derived from LULC type and slope in GEE.	Paul et al., (2019); Renard (1997)

2.6.2. Soil erodibility (K)

The Soil Erodibility (K) factor represents both susceptibility of soil to erosion and the amount and rate of runoff. Soil texture, organic matter, structure and permeability determine the erodibility of a particular soil. The K factor is calculated in Google Earth Engine using the method outlined in Table 2 in GEE having obtained data from global soils map. The erodibility factor was obtained from GEE using the procedure outlined in Fig. 2b. The code used is soil = soil.select('b0').clip(aoi).rename ('soil') Map.addLayer(soil, {min: 0, max: 100, palette: ['a52508','ff3818','fbff18','25cdff','2f35ff','0b2dab']}, 'Soil', 0); var K = soil. Expression. These were computed in the GEE platform using these predefined codes and later exported to Arc Map 10.5 in order to assess the soil erosion risk combined with other RUSLE factors. In this study, the applied soil erodibility factor in Table 3 ranged between 0.05 and 0.14 t ha h (ha MJ mm) $-^{1}$. The provided values suggest that the soils in the study area exhibit varying degrees of vulnerability to erosion.

Table 2
Description of RUSLE factors and formula.

Factors	Formula	Descriptions and purpose	Reference
R	$R = \sum_{i=1}^{12} 1.73*10^{\left(1.5*\log\left(\frac{pm^2}{pa}\right)-0.08188\right)}$	R is the rainfall erosivity in MJ mm ha−1 h−1 year−1, Pm is the monthly precipitation (mm) and Pa is the yearly precipitation (mm)	Wischmeier and Smith (1978).
K	$K = \{0.2 + 0.3*\exp\left[(-0.0256*SAN*)\left(1.0 - \frac{SIL}{100}\right)\right]\}*\left(\frac{SIL}{CLA+SIL}\right) \vert*\vert \left\{ 1 - \frac{(0.25*C)}{(C+exp)(3.72-2.95*C)}.\right\}*\left(1 - \frac{SIL0.7*Sn}{Sn+\exp(22.9*Sn-5.51)}\right)*0.1317$	CLA, SAN and SIL, are the mass fractions (%) of clay, sand, and silt,(Sn = 1 SAN/100), C is the mass fraction of soil organic carbon (%)It is the model used to determine the erosiveness of the soil	Wischmeier and Smith (1978); Alebachew et al. (2025)
LS	$LS = \left(Flow\ accumulation*\frac{(Cellsize)}{22.13}.^{0.4*}\left\{\left(\frac{Sin\ (slope)*0.01748(.)}{Sn+\exp(22.9*Sn-5.51)}\right)\right).\right\}1.4$	Slope lengthening and slope steepness factor	Renard et al.(1997)
C	$NDVI = \frac{NIR-R}{NIR+R}$ $C = \exp\left(-a\frac{NDVI}{(.\beta - NDVI)}\right)$	To assess the vegetation's capacity to protect the soil from erosion	Renard et al.(1997)
P	0.39 for agricultural lands and 1.0 for non-agricultural land (others)	To evaluate the efficacy of soil and water conservation practices in safeguarding against soil erosion	Renard et al.(1997)

A lower erodibility index (0.05) implies that the soil is relatively resistant to erosion, while a higher index (0.14) indicates a greater susceptibility to erosion processes.

2.6.3. Slope length and slope gradient

The elevation was generated using data from the Shuttle Radar Topography Mission (SRTM) derived digital elevation model (DEM). The SRTM DEM of 30m resolution was obtained from GEE platform. The data was accessed using the code var Digital = ee.Image("USGS/SRTMGL1_003″); var DEM = Digital.clip(aoi); print(DEM); var elv = DEM.select('elevation'); print(elv, 'elevation'); var slope1 = ee.Terrain.slope(elevation).clip(aoi);. The DEM was used to calculate the slope length and steepness factor (LS factor). These factors are joined as one entity in RUSLE to depict slope length (Yesuph and Dagnew, 2019). The flow accumulation and slope gradient were figured from the DEM in order to come up with the Slope length and gradient. Following that, an empirical relationship is established between these topographic characteristics and the likelihood of soil erosion in GEE (Table, 2). It is noted that soil erosion tends to increase with steeper slope gradients and longer slope lengths. The result of the slope length steepness factor (LS) ranging from 1.7 to 4848.8 suggests a wide variation in terrain characteristics within the study area (Table 3).

2.6.4. Cover management factor (C)

Determining the crop management factor (C) is crucial for evaluating the efficacy of support strategies. This factor estimates the soil loss ratio when employing support techniques compared to conventional up and downslope farming methods. The C factor was derived using the NDVI which is positively correlated with the amount of green biomass on the land (Durigon et al., 2014). Dzawanda and Ncube (2022) are of the view that, remotely sensed data provide time series data on land cover hence making it easy to derive C-factor. In this case, remotely sensed data were manipulated to derive the C factor in GEE platform for each year in the two rural dominated sub-catchments. The Sentinel 2 MSI data was used to derive the NDVI maps from bands 2 (blue), 3 (green, 10m), 4 (red, 10m), 8 (near infrared, 1m) and 11 (SWIR, 20m). The C-factor is calculated using the relevant formula of NDVI considering the red and NIR bands on the Google Earth engine. The formula used to calculate NDVI is stated in Table 2. The C factor varies from 0.001 for dense forests to 1.0 for bare land (Table 3).

2.6.5. Support practice (P)

The support practice factor (P) is an expression used to define the efficiency of the conservation practices in place for instance contouring and terracing against the intensity of surface runoff in a bid to reduce soil erosion (Paul et al., 2019). Incorporated in the RUSLE, the P factor adjusts for the effects of soil conservation practices. The P value ranges from 0 to 1 whereby '0' indicates the most relevant conservation activities and '1' indicating the least relevant. Essentially, the P factor quantifies the reduction in soil loss achieved by a particular erosion control practice compared the scenario where no such measures are implemented. To calculate the p factor, we created a code in GEE that combines the slope map with land use data. var lulc = Sentinel 2.filterDate(date1, date2).select('LC_Type1').first().clip(aoi).rename('lulc'); Map.addLayer (lulc, {}, 'lulc', 0)//Combined LULC and slope in single image var lulc_slope = lulc.addBands(slope). Specific values were assigned per land use which varies between 0 and 1. The P factor was calculated from a land use map and 0.39 for agricultural land use and 1 for other uses (Table 3).

2.7. Estimating the impact of LULC on soil erosion potential in the distinct rural landscapes

In this study, it was important to understand the link between LULC change and soil erosion occurrence and intensity. The classified LULC maps which were used as input for the RUSLE were analysed together with soil loss maps (Fig. 2a and b). In this case, the first step was to obtain samples of classified land cover types from the thematic maps derived in GEE. For each land cover samples were taken across and later produced polygon shapefiles which were later imported into the GEE cloud computing platform. Once these samples with selected pixels' values for each land cover were overlaid on the thematic soil loss maps, the researcher made use of the inspector function to estimate the soil loss values for each land cover type. This means that all the selected samples were selected each and analysed to come up with the average potential soil loss for each extracted value. The same approach was also used to establish the maximum and minimum soil loss values for each land use type per each year. This therefore enabled further statistical analysis so as to validate the findings, as it allowed for calculation of the standard deviation of annual loss values for the Shashe and Tugwi-Zibagwe sub-catchments. This attribute is important as it enables easier depiction of the dispersion of the values so that there is informed basis on the variability of soil loss in the areas.

2.8. Time series analysis-man kendall test

The Mann-Kendall test is a statistical method used to detect a monotonic (increasing or decreasing) trend in a time series of data. It is a non-parametric test that provides information about the presence and direction of a trend, as well as its statistical significance. The MK test in this study can be used to identify if there's a significant trend (increasing or decreasing) in either soil loss or NDVI values between 2016 and 2023 for both Shashe and Tugwi-Zibagwe sub-catchments, or if there's a significant correlation between the two. In essence, the MK test is a valuable tool for analysing long-term trends in soil loss and NDVI, providing insights into potential relationships between these factors.

3. Results

3.1. Accuracy assessment results

In this study, accuracy assessment was performed through the error matrix and Kappa analysis. Table 4 illustrates classification accuracies derived from Sentinel-2 analysis ready data set for the period between 2016 and 2023. The OA, based on the RF algorithm, ranged between 77 % and 91 % for Shashe, Tugwi and Zibagwe sub-catchments. The results indicated a robust contract and good accuracy based on the established thresholds. Therefore, it was inferred that the classification was implemented with good accuracy (±75 %).

The results from the Sentinel 2 MSI applied in the study yielded good UA and PA values of above 50 % for most of the land cover types in the rural dominated sub-catchments (Shashe, Tugwi and Zibagwe) for the years 2016, 2020 and 2023. In line with this, the highest PA of 100 %, using Sentinel-2, were obtained for water class and plantation for the years 2020 and 2023 which demonstrates good agreements, whereas lower PA values 66 % were obtained for grasslands in 2020 for the Shashe sub-catchment (Table 4). For the Tugwi-Zibagwe sub-catchment water and plantation recorded high PA for Sentinel-2 (100 %) for the years 2020 and 2023, with the least values being obtained for grasslands (60 %) for 2020. During the same period under study, for the Shashe water had the highest UA of 100 % with grasslands recording 60 % which was the lowest in the year 2020 compared to the other land classes. For the Tugwi-Zibagwe higher values for UA were obtained for water and built-up areas (100 %), with the lowest that is 60 % being recorded for grasslands in 2023. In terms of kappa statistics, the values were above 50 % for both Shashe and Tugwi-Zibagwe sub-catchments. The highest kappa value was recorded for woodlands in 2020 for the Shashe sub-catchment with the results being above 70 % which shows strong agreement (Table 4).

3.2. LULC changes in the rural dominated sub-catchments

The study findings revealed that machine learning coupled with

Table 4
LULC classification accuracy for Shashe, Tugwi- Zibagwe sub-catchment over the years.

Sub-catchment name	Year	Land cover class	PA	UA	Kappa
Shashe	2016	Water	100	100	87
		Plantation	77.2	89.4	76
		Cultivated	100	83.72	75
		Grasslands	90	85.71	76.76
		Woodlands	78	88	77
		Eroded areas	80	83.33	76.85
		Built-up	53.33	80	76
	2020	Water	100	100	78
		Plantation	100	100	95
		Cultivated	86.36	67.85	70
		Grasslands	66.66	63.15	70
		Woodlands	85.18	85.16	75.71
		Eroded areas	90	66.66	50
		Built-up	67	78	75
	2023	Water	100	100	78
		Plantation	81.2	92.81	78.2
		Cultivated	90	79.41	80
		Grasslands	78	77.91	78
		Woodlands	91.17	89.85	91.17
		Eroded areas	80	85.71	75
		Built-up	76.66	80	77.66
Tugwi-Zibagwe	2016	Water	100	100	88
		Plantation	76.9	71.4	78
		Cultivated	87.5	87.5	77.5
		Grasslands	87.1	75	75.4
		Woodlands	78.9	75	87.8
		Eroded areas	85.72	52.85	83.33
		Built-up	100	100	70.7
	2020	Water	100	100	76
		Plantation	100	97.22	77
		Cultivated	100	95.55	76
		Grasslands	67.66	66.66	70
		Woodlands	96	84.4	76
		Eroded areas	90	70	76
		Built-up	73.33	100	75
	2023	Water	100	100	78
		Plantation	100	100	79
		Cultivated	87.5	80.7	72
		Grasslands	89.4	60	76
		Woodlands	87.8	96.6	75
		Eroded areas	83.33	62	76
		Built-up	70.7	80.33	70

Sentinel-2 analysis ready blue sky data sets (2016, 2020 and 2023) produces accurate results. These results show that there are seven land covers which vary in Shashe and Tugwi–Zibagwe sub-catchments. The LULC changes for both sub-catchments are presented in Fig. 3a and b and Table 5.

The results show that the most dominant cover for the Shashe sub-catchment in 2016 was woodlands which occupied 28.81 %, followed by plantation occupying 25.49 %. Cultivated lands also occupied 24.49 % of the total sub-catchment, whilst eroded areas were reported to occupy 3.11 %. The least class in the Shashe sub-catchment was the area occupied by water (1.3 %). This was slightly different from Tugwi-Zibagwe sub-catchment where, grassland was the predominant land cover as it occupied 45.51 % of the total land area in 2016, followed by woodlands covering 25.2 % (Table 5). Eroded areas were observed along major drainage networks and areas with poor soil characteristics which had potential to result in loss of top soil cover hence leading to further degradation, especially in the central to northern parts (Fig. 3a). In this case, poor soil characteristics refer to a range of negative traits in soil that hinder its ability to support healthy plant growth and overall ecosystem function. These characteristics can impact soil fertility, structure, drainage, and other vital properties rendering the soil unable to support plant growth hence exposed to erosion. Eroded areas which were the focus of the study occupied 2 % in the same year. The least class among all other classes was built-up areas covering 1.8 % which however increased to 3.32 % in 2020. However, in both sub-catchments, grassland cover constituted an integral component compared to other LULC types (Table 5).

The results of the study clearly depict that there were significant LULC changes marked by an increase in the area occupied by cultivated areas from 24.49 % (2016) to 27.88 % in 2020 for the Shashe sub-catchment. This increase was at the expense of plantation area which largely decreased from 24.88 % to 5.89 % which shows a decrease of 76.2 %. In addition, woodlands which covered 20.82 % in 2016 decreased to 9.93 % of the total area which translated into a loss of 52.46 % (Table 5). Comparatively, the area covered by grasslands increased by 8.3 % of the total sub-catchment area in 2020. The dominant land cover change between 2016 and 2020 was reported for eroded areas. The area covered by eroded surfaces increased by 60.38 % in the year 2020. This was at the expense of the area covered by water, grasslands and woodlands as some areas were cleared for development and cultivation in the rural dominated sub-catchment hence open areas

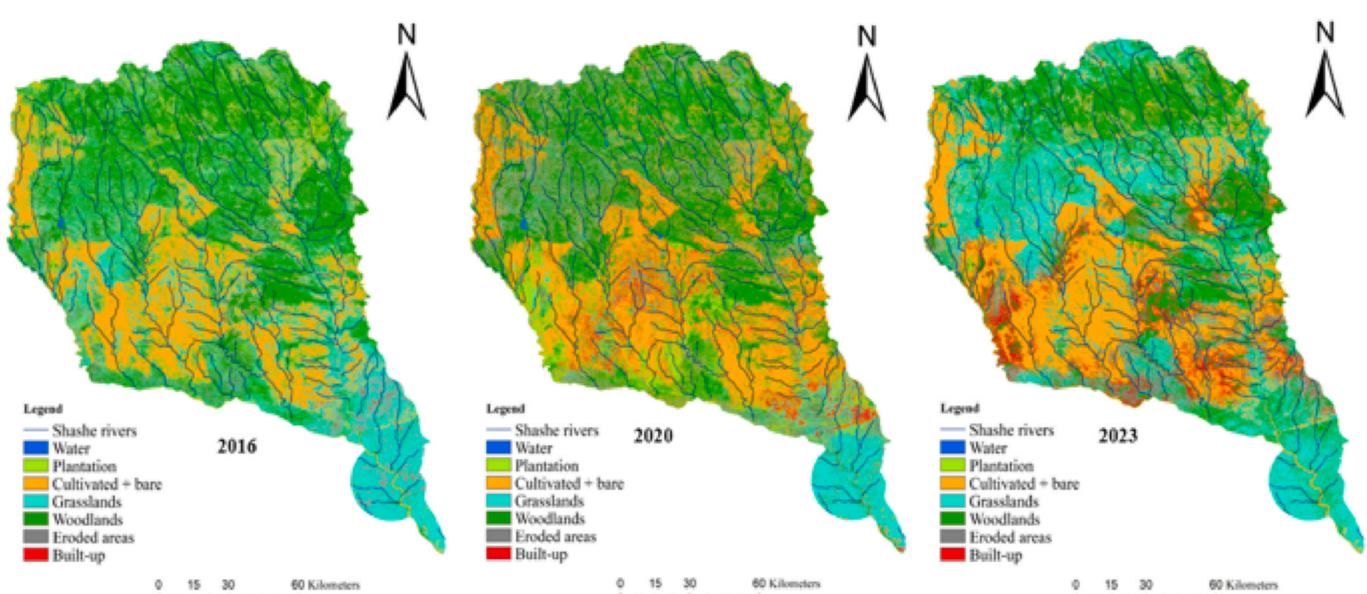

Fig. 3a. Derived LULC maps to show the LULC types in Shashe sub-catchment in different years.

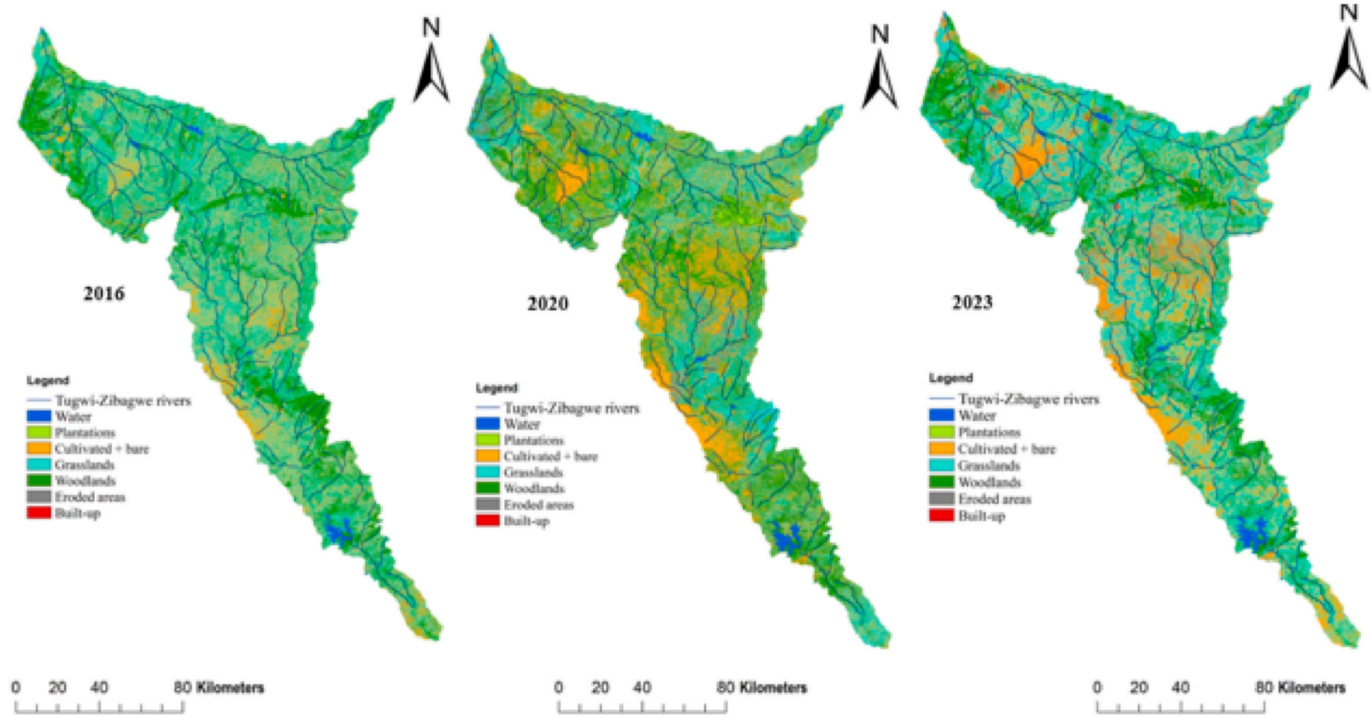

Fig. 3b. Derived LULC maps to show the LULC types in Tugwi-Zibagwe sub-catchment in different years

Table 5
LULC change in Shashe and Tugwi –Zibagwe rural dominated sub-catchments (measured in km^2 and proportion of change in percentages) between 2016 and 2023.

Sub-catchment name	Land cover type	2016 Area (km^2)	2020 Area (km^2)	Change Area (km^2)	% Change	2023 Area (km^2)	Change Area (km^2)	% Change
Shashe	Water	247 (1.3)	7.901 (0.04)	229.34	−89.81	19 (0.10)	11	0.15
	Plantation	4733 (25.49)	1122 (5.89)	3611.90	−76.20	1843 (9.68)	721	64.29
	Cultivated + bare	4850 (24.49)	4925 (27.88)	74.83	1.54	6777 (35.62)	1851	37.59
	Grasslands	3998 (22.82)	1890 (9.93)	2040.65	−52.28	5418 (28.47)	3527	86.54
	Woodlands	5102 (28.81)	5527 (29)	425.04	8.33	2071 (10.88)	3456	−62.52
	Eroded areas	392 (2.11)	4166 (18.89)	3474.65	40.38	3127 (16.43)	447.367	−10.73
	Built-up	535 (1.81)	631 (3.32)	98.528	18.40	618 (3.24)	13.368	2.11
Tugwi –Zibagwe	Water	700 (4.10)	105 (0.71)	794.41	−88.26	112 (0.75)	658	12.65
	Plantation	1687 (11)	37 (0.25)	1649.37	−97.76	69 (0.46)	31.516	83.46
	Cultivated + bare	2105 (17.27)	1711 (11.59)	393.5	−18.68	3151 (21.36)	1439.85	84.10
	Grasslands	6714 (43.51)	9610 (65.14)	2895.50	−43.12	6157 (41.73)	3452.21	35.92
	Woodlands	2924 (25.2)	2175 (14.74)	748.51	−0.25	4653 (31.54)	2478.29	113.91
	Eroded areas	230 (1.23)	830 (5.62)	546.51	92.77	199 (1.34)	630.902	−76
	Built-up	283 (1.7)	380 (2.57)	50.3	15.21	406 (2.75)	26.031	6.83

were exposed.

In Tugwi–Zibagwe sub-catchment, grassland area which covered 43.51 % in 2016 increased to 65.14 % in 2020 which accounts for an increase of 43.12 %. The same land cover reduced by 43.92 % in the year 2020 which can be attributed to increase in the area covered by cultivation. Cultivated area increased which was accompanied by a significant decrease in the area covered by water from 2020 although it increased by small proportions in the year 2023 due to improved rainfall patterns across the sub-catchment area (Fig. 3b). The area covered by plantation reduced by 97 % for the year 2020 and while cultivation significantly increased by the year 2023 due to increases in precipitation which enhanced the activities linked to this land cover. The area covered by woodlands also increased while at the expense of plantation areas which saw a decrease due to deforestation practices mainly for timber logging. Deforestation was observed to be presenting serious challenges which is unchecked would reduce ground cover hence increasing susceptibility to soil erosion risk.

Conversely, plantation areas which occupied decreased from 11.43 % in the year 2016 to 0.25 % in 2020 and 0.46 % in 2023 (Table 5). The area covered by erosion shows a significant increase of 92.77 % although at the expense of woodlands and grasslands areas which significantly reduced between 2016 and 2020 in the Tugwi–Zibagwe sub-catchment area. This could be attributed to land conversion for other land uses which resulted in creation of bare surfaces hence exposing the soil to the various agencies of erosion. Soil erosion was therefore observed to be increasing from 2016 to 2020 especially along cultivated land. Areas with severe degradation were also detected in Chivi district as top soil is washed away. This can be attributed to extensive grazing which exposes the soils to various agencies of erosion. Therefore, the problem is not grazing but the incorrect grazing management. It is clear that, all the sub-catchments experienced noticeable LULC especially cultivated areas, grasslands and woodlands in the past decade. For both sub-catchments, cultivated areas recorded the most significant increase followed by woodlands and grasslands while at the expense of water cover which reduced remarkably. In the Shashe sub-catchment, dominant changes in areas covered by erosion were observed in 2016 as a result of land conversion for several use. The purpose for clearing land in Tugwi–Zibagwe was mainly for logging activities and agriculture.

3.3. Assessing the potential soil loss risk using RUSLE model in the sub-catchments

RUSLE factor parameter raster maps were fused to produce the thematic soil loss maps (2016, 2020 and 2023) for the Shashe and Tugwi–Zibagwe sub-catchments respectively. The Shashe and Tugwi–Zibagwe sub-catchments were divided into five soil erosion risk classes that is from slight to severe.

Results show that, soil loss ranged from 0 to over 100 t ha^{-1} $year^{-1}$ (Fig. 4a and b). It can also be noted that the lowest risk of erosion had an annual soil loss of 10 t ha^{-1} $year^{-1}$ and highest risk >100 t ha^{-1} $year^{-1}$ for the Shashe sub-catchment (Fig. 4a). The highest risk of soil erosion tends to be more concentrated in the north-eastern parts especially for the Shashe sub-catchment and along drainage networks. Comparatively, the Tugwi –Zibagwe had considerable high erosion risk on the central and southern parts mainly around agricultural fields in communal areas. In the Tugwi–Zibagwe sub-catchment the lowest risk of erosion was observed to be 8 t ha^{-1} $year^{-1}$ and highest risk of erosion reaching 100 t ha^{-1} $year^{-1}$ (Fig. 4b).

The areas containing agricultural fields which were exposed to tillage methods displayed the greatest soil erosion potential. These areas had significantly high C values. Most of these areas are located on the Northern parts of the Shashe and for the Tugwi–Zibagwe on the south-western parts (Fig. 4a and b). Areas on gentle slopes had tolerable levels of erosion as the slope would provide conditions that prevent the soil from being lost.

Tables 6 and 7, depict the soil loss dispersal in the rural dominated sub-catchments spread across five severity classes. The study findings show that in 2016 about 84.7 % of the Shashe sub-catchment had slight of soil erosion rates, whereas moderate and high rates accounted for 13.9 % and 0.9 % respectively. Comparatively, the areas affected by very high and severe soil loss rates occupied 0.5 % of the sub-catchment (Table 6). The soil rates somewhat changed in the year 2020, as areas with slight erosion occupied 8.9 % and moderate soil erosion covering 80.4 % whereas high (6.9 %) and severe erosion occupied 1.8 % of the sub-catchment.

Results demonstrate that, in the Tugwi –Zibagwe sub-catchment area it is evident that the central and southern parts are more eroded due to crop cultivation and proliferation of artisanal mining operations. The study findings further show that in 2016 about 86 % of the Tugwi-Zibagwe sub-catchment had slight soil loss, whereas areas affected by moderate rates encompass 12.5 %. However, high erosion hazard pockets were reported to be a common feature on the north-eastern parts of the study area (0.9 %) due to the expansion of settlements. Additionally, areas with very high and severe rates of erosion which require intervention occupied 0.6 % of the total sub-catchment (Table 7). Further, severe erosion was experienced on (0.3 and 0.2 %) respectively for the Tugwi-Zibagwe sub-catchment (Table 7).

Comparatively, the Shashe sub-catchment area is experiencing high rates of erosion with units of dispersion indicating the ranges. Interestingly, the soil rates show some changes with regards to the classes of erosion rates in Tugwi–Zibagwe sub-catchment. For instance, in the year 2023 areas with slight erosion occupied 62.4 % and moderate soil erosion covering 36 % whereas high and severe occupied 0.6 % of the total sub-catchment area. The results clearly indicate severe soil loss was generated on the central part (Fig. 4a). Elsewhere, low levels of erosion could be observed in areas with gentle slopes and low cover management factor. Results also revealed that, in terms of priority for conservation, the areas experiencing slight erosion risk are not in dire need of restoration. On the other extreme, it is clear that areas experiencing severe erosion should be given priority as there is urgent need to restore these disturbed areas in the rural dominated sub-catchments in Zimbabwe.

3.4. Impact of changing land-use patterns on soil erosion occurrence and intensity

The Shashe sub-catchment showed mean soil losses of 15.75, 45.25, and 23.51 t ha^{-1} $year^{-1}$ for 2016, 2020, and 2023, respectively. Results in Table 8 show erosion accelerated by LULC change over the study period and demonstrates fluctuations on the rate of soil loss based on the units of dispersal shown (Table 8). It is clear that cultivated + bare land which is cleared in all the distinct landscapes (2016, 2020 and 2023) appears to have maximum soil loss values which tend to be increasing 55–70 t ha^{-1} $year^{-1}$ (Table 8) with the highest being recorded for the year 2020. For example, in Shashe, cultivated land which occupied a significant proportion was exposed to severe soil erosion with minimum values being recorded on plantation (3 t ha^{-1} $year^{-1}$ (Table 8) and areas covered by water. In its strict sense, higher soil loss tends to be recorded in areas with crops attributed to intensive ploughing using mould board ploughs which turn the soils over hence affecting the texture. Similar to this, the area under plantation also experienced moderate to high

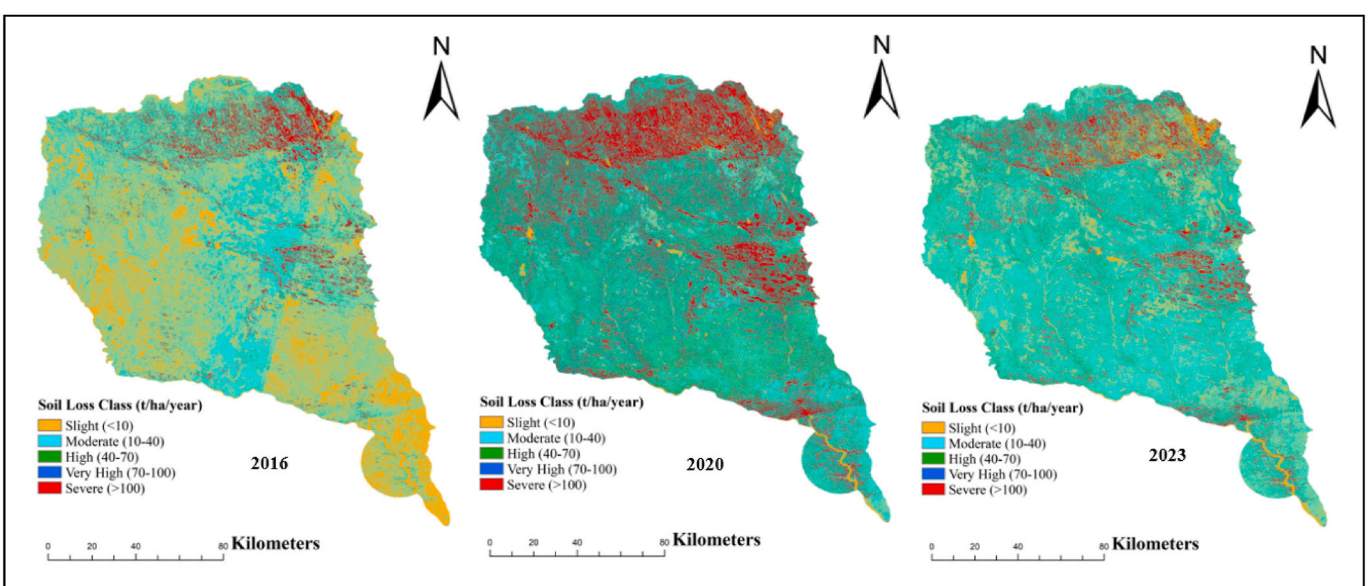

Fig. 4a. Map showing spatial variations of soil loss in Shashe sub-catchment.

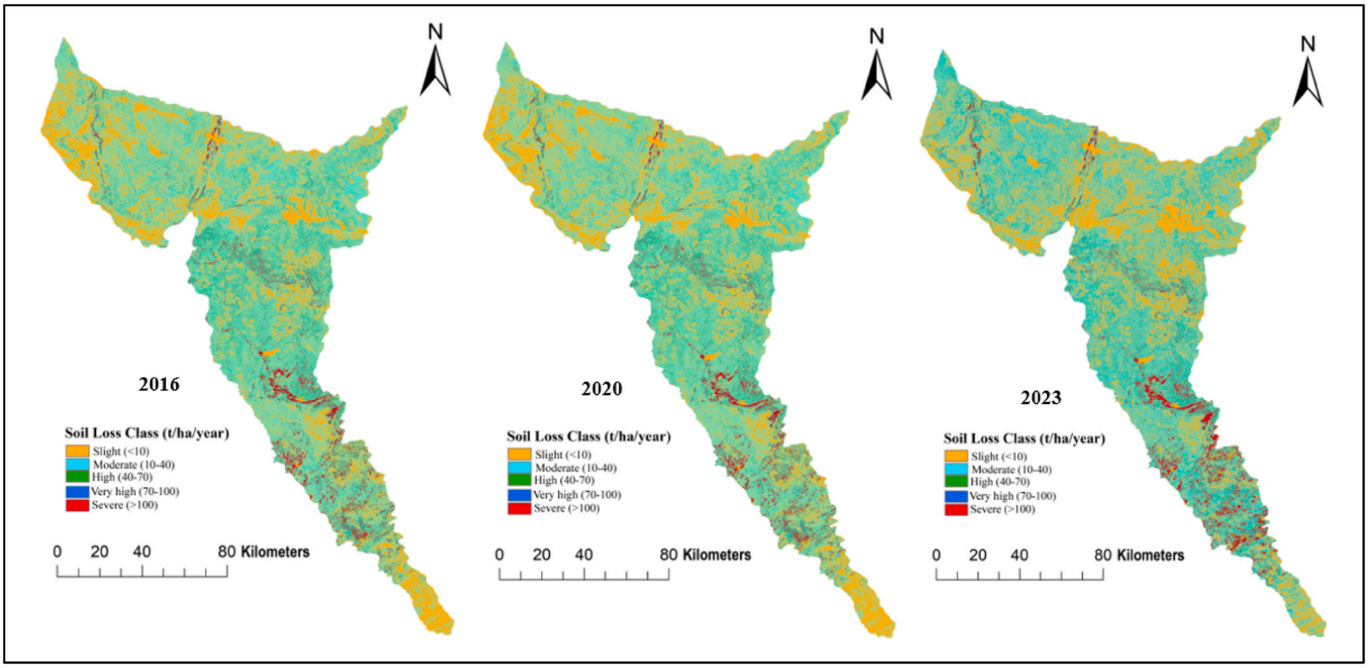

Fig. 4b. Map showing spatial variations of soil loss in Tugwi-Zibagwe sub-catchment.

Table 6
Annual soil erosion rates and area coverage in the Shashe sub-catchment.

Soil loss rates (t ha^{-1} year^{-1})	Severity classes	Area (km^2) experiencing soil loss in Shashe sub-catchment			Percent of total		
		2016	2020	2023	2016	2020	2023
<10	Slight	16,109	1700	6998	84.7	8.9	36.8
10–40	Moderate	2650	15,290	11,561	13.9	80.4	60.8
40–70	High	165	1314	361	0.9	6.9	1.9
70–100	Very high	53	376	69	0.3	2	0.4
>100	Severe	47	344	35	0.2	1.8	0.2

Table 7
Annual soil erosion rates and area coverage in Tugwi –Zibagwe sub-catchment.

Soil loss rates (t ha^{-1} year^{-1})	Severity classes	Area (km^2) experiencing soil loss in Tugwi –Zibagwe sub-catchment			Percent of total		
		2016	2020	2023	2016	2020	2023
<10	Slight	12,686	12,378	9209	86	83.9	62.4
10–40	Moderate	1850	2259	5317	12.5	15.3	36
40–70	High	137	86	162	0.9	0.6	1.1
70–100	Very high	39	19	38	0.3	0.1	0.3
>100	Severe	39	8	25	0.3	0.1	0.2

erosion which averaged between 9 and 15 t ha^{-1} year^{-1}.The same cover recorded maximum soil loss values of 18 t ha^{-1} year^{-1} (Table 8) which increased to about 36 t ha^{-1} year^{-1} (Table 8) between 2016 and 2020 which clearly shows that temporal LULC changes were also a significant factors in as far as soil loss risk is concerned in Shashe sub-catchment.

Another noticeable example of the impact of LULC was on grasslands (mainly used for grazing) which experienced an average loss of 12–20 t ha^{-1} year^{-1} (Table 8). This same land cover also experienced maximum soil loss values which increased from 20 to 35 t ha^{-1} year^{-1} (Table 8) between 2016 and 2023 which was the highest for this cover. This was followed by the area under woodlands which were observed to be disappearing. It is clear that, slight to moderate erosion was experienced in areas covered by woodlands although they were observed to be threatened by deforestation. As the area covered by woodlands decreased there was exposure to erosion which averaged between 10 and 17 t ha^{-1} year^{-1}. The area covered by woodlands recorded and increase from 27 to 30 t ha^{-1} year^{-1} (Table 8) with a standard deviation of 7 as shown by the units of dispersion. Soil erosion potential was also observed in areas covered by water and built-up areas although not severe when compared to others. These two respective land classes had an annual average loss that ranged between 1 and 5 t ha^{-1} year^{-1}. In some cases, the areas surrounding these land covers also recorded maximum soil loss between 3 and 9 t ha^{-1} year^{-1} (Table 8) which shows that there was an increase in the soil erosion risk with time that is attributed to LULC in the Shashe sub-catchment area.

Table 8
Summary of soil loss values from each land use over time in Shashe sub-catchment.

Land Cover/Use Type	Unit of dispersion per each Land cover per year (t/ha/year)											
	2015				2020				2023			
	Min	Mean	Max	SD	Min	Mean	Max	SD	Min	Mean	Max	SD
Water	1	2.23	4	0.75	0.80	4	3	13	0.30	1.78	3	0.65
Plantation	3	9	18	3.75	5	18	36	7.75	6	15	35	7.25
Cultivated + bare	7	27	55	12	3	48	70	16.75	7	38	60	13.25
Grasslands	4	12	20	4	3	20	30	6.75	2	13	35	8.25
Woodlands	3	10	27	6	2	17	30	7	3	12	25	5.5
Eroded area	4	15	25	5.25	6	20	45	9.75	4	13	26	5.5
Built-up area	0.5	1.88	4	0.87	2	7.5	3	2.5	2	5	9	1.75

Table 9
Summary of soil loss values from each land use over time in Tugwi-Zibagwe sub-catchment.

Land Cover/Use Type	Unit of dispersion per each Land cover per year (t/ha/year)											
	2016				2020				2023			
	Min	Mean	Max	SD	Min	Mean	Max	SD	Min	Mean	Max	SD
Water	0.40	2	3	0.65	1	3	6	1.25	1	5	7	1.5
Plantation	2	6	11	2.25	2	8	15	3.25	2	7	13	2.75
Cultivated + bare	5	16	30	6.25	8	25	56	12	7	21	42	8.75
Grasslands	3	9	18	3.75	4	11	23	4.75	2	8	15	3.25
Woodlands	4	9	19	3.75	5	15	29	6	4	10	19	3.75
Eroded area	1	5	9	2	4	10	21	4.25	3	14	27	24
Built-up area	0.4	1.56	3	0.65	1	5.67	9	2	1	4.57	8	1.75

In the Tugwi-Zibagwe sub-catchment, mean soil losses recorded were 11.62, 18.45, and 37.34 t ha^{-1} $year^{-1}$ for the years 2016, 2020 and 2023 (Table 9). Comparatively, findings show that of all land covers in Tugwi-Zibagwe, the area under cultivation experienced high soil erosion risk which averaged between 16 and 21 t ha^{-1} $year^{-1}$. This same land cover in 2020 obtained maximum values of 56 t ha^{-1} $year^{-1}$. This maximum was however reduced in the year 2023 to 42 t ha^{-1} $year^{-1}$ although at the expense of other land cover type due to improper farming and cultivation activities which often expose the soil to agents of erosion. This clearly shows that the areas under cultivation which are often cleared increase the magnitude of soil erosion on the rural dominated areas. Similarly, another land cover type that experienced soil loss is grasslands which had a maximum of 18 t ha^{-1} $year^{-1}$ for the year 2016 (Table 9), with minimum values ranging between 2 and 3 t ha^{-1} $year^{-1}$ which signify the increasing trend of soil loss over time and with changing land use cover.

Results based on dispersion values to provide a more nuanced view of the impact of LULC also show that woodlands were affected by erosion. Results of LULC maps show that this cover was observed to be reducing with time which undoubtedly left room for erosion as the size reduced from 2010 to 2023 in the areas to the south western parts (Fig. 3b). In this manner, the area covered by woodlands which was decreasing had maximum soil loss values of 19 t ha^{-1} $year^{-1.}$ In the year 2016, which further increased due to reduction in size of the area recording maximum soil loss values of 29 t ha^{-1} $year^{-1}$ which clearly shows that the LULC had a bearing in as far as soil erosion occurrence and intensity is concerned in the Tugwi-Zibagwe sub-catchment. Results from the LULC of 2010, 2020 and 2023 show that water was also affected by soil erosion which averaged between 2 and 5 t ha^{-1} $year^{-1}$. Similar to this, the area under built up were increasing as a result of encroachment in pristine areas as local people established settlements especially in areas close to drainage networks which had potential to increase soil erosion rates. Soil erosion in the Shashe and Tugwi–Zibagwe sub-catchment resulted in the loss of soil fertility.

The Mann-Kendall test results indicated no statistically significant changes in both NDVI (Kendall tau slope = 0.36; p = 0.28) and annual soil loss (Kendall tau = 0.26; p = 0.63) in the Shashe sub-catchment. This shows that NDVI values were declining but not following a statistically significant ($p > 0.05$) (Table 9) trend whilst annual soil loss was generally declining when compared to the 2016 and 2020 years. This shows that NDVI values which are an indicator of vegetation health was declining but not following a statistically significant trend whilst soil loss was generally declining when compared to the 201–2020 scenarios. Results in Table 9 further show that, just like the Tugwi-Zibagwe sub-catchment there were no statistically significant changes in both NDVI (Kendall tau slope = 0.33; p = 0.20) and annual soil loss (Kendall tau = 0.11; p = 0.57). This also clearly shows that NDVI values were declining but not following a statistically significant ($p > 0.05$) (Table 10) trend whilst annual soil loss was generally declining when compared to the 2016 and 2020 years.

Table 10
Summary of Mann-Kendal Tests for the Shashe and Tugwi-Zibagwe sub-catchments.

Shashe sub-catchment	Variable/parameter	Kendall's tau	p-value
	NDVI	0.36	0.28
	Mean annual soil loss	0.26	0.63
Tugwi-Zibagwe sub-catchment	Variable/parameter	Kendall's tau	p-value
	NDVI	0.33	0.20
	Mean annual soil loss	0.11	0.57

4. Discussion

4.1. LULC changes in the rural dominated sub-catchments

The study aimed to model potential soil erosion in two distinct rural landscapes in Zimbabwe. Thus, the primary objectives are to: assess spatio-temporal LULC changes in distinct rural landscapes; assess the soil erosion risk using a multi-pronged approach. Results clearly demonstrate that Analysis ready data sets (Sentinel 2) combined with RF classification algorithm can accurately map LULC. The results clearly depict that there are land covers which vary as a result of several changes which have occurred in the rural landscapes. OA of the analysis ready data for the Shashe and Tugwi–Zibagwe sub-catchment classified maps is (±75 %). Likewise, the kappa coefficient ranged between 70 % and 92 % respectively which indicated good accuracy based on the established thresholds (Obiahu and Elias, 2020). High PA and UA were observed for the Shashe sub-catchment for the years 2020 and 2023, with low values around 60 % being recorded for land covers such as grasslands. It is therefore, clear that the accuracies derived were within the suitable ranges as indicated in previous studies by Gwitira et al. (2016). Thus, the results were more accurate, an attribute which is essential as it brings confidence to the users as well as aid in promulgation of soil conservation strategies. This also demonstrates the study's significance as it integrates high resolution data (Sentinel 2) with machine learning approaches which improved the accuracy thus also enhancing the quality of assessments a feature missing in other previous soil erosion studies conducted.

This work showed that the most dominant cover for the Shashe sub-catchment in 2016 was woodlands, followed by plantation areas. The least dominant class reported for the Shashe sub-catchment was the area occupied by water owing to changing rainfall patterns in the area. However, there has been marked decrease in the area covered by the grasslands as it is used for various activities such as uncontrolled livestock grazing. Such practices have a significant bearing as vegetation is cleared and also subjected to cattle trampling which increases the rate of soil erosion. As such, the problem of erosion continues to be experienced if there is incorrect grazing management hence the need for controlled and planned grazing. This clearly shows that a combination of social and environmental factors drives land use change, a situation which has potential to influence the rate and intensity of soil erosion in sub-catchment areas. Similarly, Paul et al., (2019) observed that LULC changes tend to vary from time to time as a result of hence affecting the rate of soil erosion. This position was slightly different from Tugwi –Zibagwe sub-catchment where, cultivated area was the predominant land cover as it occupied about 43.5 % of the sub-catchment in 2016.

The major differences in the land covers observed can be attributed to drivers such as population growth, settlement expansion and land clearance for agriculture to boost food production (Ota et al., 2024). Previous studies in Zimbabwe, for example Dzawanda and Ncube (2022), revealed that sustainable food production is yet to match with population increase as most people are food insecure. This therefore clearly shows that there is need to integrate the environmental and socio-economic factors into soil erosion risk models to enhance decision making. Increased artisanal activities in the sub-catchment areas (Tugwi) also resulted in vegetation clearance. Therefore, LULC have negative impacts on biodiversity status which requires intervention (Abdulkareem et al., 2019). A study by Obiahu and Elias (2020) in Nigeria proved that there is need to come up with a set of strategies that can be aligned into land use planning and conservation strategies so as to address the socio-economic drivers of land use changes which are the main drivers of soil erosion.

Results demonstrate that eroded areas are more common along major drainage networks and areas which cannot support plant growth in Shashe sub-catchment. The central to northern parts of the sub-catchments had potential to result in loss of top soil cover accelerating further degradation. Dube et al. (2017) observed that in King Sabata weak soils are prone to severe degradation which complicates efforts aimed at promoting at conserving natural resources. The central part of the Tugwi was exposed to severe erosion as top soil is washed away. The underlying causes include extensive grazing which exposes the soils to erosion. Therefore, it can be concluded that this combined with cattle trampling loosened soils affecting the geomorphology of the area as the soil is vulnerable (Musasa et al., 2024).

4.2. Assessing the potential soil loss risk in the sub-catchments

The results derived from this study indicate that the sub-catchments suffer from unprecedented soil losses, ranging from 10 t ha^{-1} year^{-1} and >100 t ha^{-1} year^{-1}. These high values far exceed the estimated mean soil loss tolerance rates proposed across the world which range between 12 and 15 t ha^{-1} year^{-1} which shows that the sub-catchment under study have been experiencing severe soil loss (Ashiagbor et al., 2013). This increased soil loss risk has potential to affect soil physical characteristics which may result in reduced fertility rendering the soils unproductive for agriculture. The erosion hazard maps for 2016 and 2023 in Shashe show that a small portion covered by water in the sub-catchment was in the low erosion hazard class, which aligns with findings by Paul et al., which also adopted RUSLE and machine learning approaches. However, the risk of erosion tends to be more concentrated in the north-eastern parts of the study areas, especially for the Shashe sub-catchment and along drainage networks. This was due to the expansion of settlements as well as land clearance for several purposes, deforestation was high as a result of increased demand for firewood for commercial uses a position also confirmed by Dzawanda and Ncube (2022). In the Tugwi–Zibagwe sub-catchment it was found that the areas with high slope gradient and high C values were associated with high annual soil loss.

Results further show that the Western parts of the Shashe and Tugwi –Zibagwe sub-catchments had slight erosion. As a result, especially for the Tugwi –Zibagwe there is controlled grazing, area closure, terrace, grass strip management which has enabled restoration efforts. These different strategies employed by the local community in the distinct rural landscapes were aiding in restoration of degraded areas. Similar to this, findings from a study by Yesuph and Dagnew (2019) in the Gedalas watershed located in Ethiopia indicated that local communities as custodians employ various strategies to control soil erosion. It is clear that areas experiencing severe risk of annual soil loss (>100 t ha^{-1} year^{-1}) are in dire need of SLM practices. Areas experiencing severe erosion in the Tugwi–Zibagwe sub-catchment were occupied by crop lands and in some cases on bare surfaces which are exposed to soil erosion which calls for the need to come up with interventions to foster sustainable development.

It is clear that, slope angle and slope length significantly influenced soil erosion rates in the Shashe and Tugwi –Zibagwe sub-catchments. A clear view from a slopes dimension, shows that soil loss becomes more pronounced as slope gradient increases across. The areas with slope gradients that were higher than 65 % were observed to experience severe soil loss rates. As such, these factors trigger soil erosion compounded by improper land management practices (Abdulkareem et al., 2019). This finding is in agreement with Paul et al., (2019) and Phinzi et al. (2021) who reported that in case of high erosion hazard, contouring methods should be put in place. In the Tugwi–Zibagwe sub-catchment the slope is more even when compared to Shashe sub-catchment hence resulting in tolerable values of soil loss. Differences in severity classes of soil loss risk were also observed across both Shashe and Tugwi–Zibagwe sub-catchments and had potential to result in further degradation if unchecked. It is clear that areas experiencing severe risk of annual soil loss (>100 t ha^{-1} year^{-1}) are in dire need of sustainable land management (SLM) practices. Areas experiencing severe erosion in the Tugwi–Zibagwe sub-catchment were occupied by crop lands and in some cases bare surfaces.

4.3. Impact of changing land-use patterns on soil erosion occurrence and intensity

The study findings reveal that changing land use patterns influence the extent of soil erosion in rural dominated sub-catchments. The findings clearly show that soil losses were considerably high for cultivated + bare land areas. Similarly, Abdulkareem et al. (2019), reported that higher soil loss values are experienced in areas with crops where cultivation on steep slopes and intensive ploughing is practiced. This arguably turns the soils over hence affecting the geomorphology of the area hence increasing the frequency and extent of erosion (Yesuph and Dagnew, 2019; Marondedze and Schütt, 2020). Additionally, slight to moderate erosion was experienced in areas covered by woodlands threatened by deforestation a position also confirmed by Paul et al., (2019). However, changes in land use patterns for instance clearance of forested areas to promote cultivation affected the soil texture and ability to with stand erosive agents. The end result is increased frequency and intensity of erosion which continues to present problems. Analysis of the above information clearly shows that there are variations in the rate of soil loss which can be necessitated by changing land use patterns over time hence the need to come up with restoration activities especially for rural dominated areas.

Soil erosion in the Shashe and Tugwi –Zibagwe sub-catchment is largely driven by agricultural activities, mining and uncontrolled livestock grazing which have become a cause of concern. These activities were reported to disturb the ground which increases the potential rates of erosion thus reducing fertility. Results also show that, other land covers such as woodlands and grasslands were also affected by soil loss due to vegetation clearance as a result of human activities. As the area covered by woodlands decreased there was exposure to erosion which averaged between 10 and 17 t ha^{-1} year^{-1}. It is clear that, if no meaningful efforts are put in place soil loss will surpass the rate of soil formation which has negative implications on food security (Yesuph and Dagnew, 2019; Dzawanda and Ncube, 2022). This will also negatively affect biodiversity in the area a position confirmed by Paul et al., (2019) as well as efforts aimed at attaining SDGs for instance 1 and 2 on ending poverty and zero hunger respectively. In the Tugwi–Zibagwe sub-catchment logging activities are also common hence leading to reduced vegetation cover which in the end expose the soil to erosion as indicated by the increase in the maximum soil loss values spread across the various land covers. In Tugwi–Zibagwe sub-catchments, construction activities resulted in clearance of ground vegetative cover which exposed soil to erosion. This is in response to the growing demand for settlement in order to meet the growing demand at the expense of areas covered by woodlands and plantation areas which were declining. Settlement establishment results in clearance of large tracts of lands which results in areas devoid of vegetation (Dzawanda and Ncube, 2022).

The Mann-Kendall test results indicated no statistically significant changes in both NDVI) and annual soil loss for both the Shashe and Tugwi-Zibagwe sub-catchment. This generally shows that NDVI values were declining but not following a statistically significant trend. This aligns with findings of Phinzi et al. (2021) who observed that changes in NDVI values over time can be used to assess soil loss as was the case and generally do not follow a significant trend. Results further show that, whilst annual soil loss was generally declining when compared to the 2016 and 2020 years. The major reasons for this can be attributed to various factors such as the establishment of a series of conservation strategies. Musasa et al. (2024) opines that soil loss is generally low in areas that do not experience excessive cultivation and have controlled grazing. These findings offer valuable insights into soil erosion variations, which thus supports sustainable soil management practices and informing erosion control strategies. The results of the study also contribute to land use planning and policy development aimed at mitigating soil degradation and enhancing agricultural resilience in rural dominated sub-catchments of Zimbabwe.

4.4. Limitations of the study and the need for future research

Despite an attempt to improve the spatial resolution, not all soil erosion features have been classified, for example rills, sheet and some small gullies have been excluded possibly because their sizes fall below the spatial resolution (10m) of the data sets used e.g the Sentinel 2 MSI. Within the respective sub-catchments, the spectral reflectivity of soil erosion features tends to vary, and in some cases tends to be like non-erosion features (for example, bare soil). This therefore creates room for the possibility of classifying some soil erosion features as non-erosion features. For example, the spectral reflectance of sheet erosion may resemble that of bare soil surfaces making it difficult if not impossible to spectrally discriminate between the two features. This therefore, calls for the need for longitudinal researches that continue to explore ways that can be used to improve the quality of assessments so as to enhance decision making hence better environmental management.

The study also relies on remotely sensed data and GIS-based modelling for soil erosion estimation. This therefore, limited full scale field-based validation of erosion risk although not absent as it was conducted within a specific period of time. It is also important to note that, the Revised Universal Soil Loss Equation (RUSLE) model includes several empirical factors (e.g., R, K, LS, C, P) and these were derived from secondary data for instance rainfall data from CHIRPS. These assumptions may introduce uncertainties which may affect the quality of soil erosion assessments. Empirical models are easy to use hence widely applied, especially in areas with limited data availability. As such, each model suits well depending on the particular context within which it can be applied. For instance, without the integration of geospatial techniques such as GIS and remote sensing techniques, the model does not assess soil erosion in spatial context (Habtu and Jayappa, 2022). This clearly shows that on its own the model is not sufficient in soil erosion modelling due to issues of complexity, for instance, terrain variables. Recently, Phinzi et al. (2021) obtained low accuracies from the RUSLE model results as it overlooked the concept of erosion in areas with gentle slope in the catchment as gully erosion was largely active. These limitations suggest the need for further studies to generate comprehensive evidences for proper decisions.

5. Conclusions

The present article fused a combination of robust remote sensing methods and RUSLE approach to appreciate soil erosion risk under varying LULC circumstances between 2016 and 2023. The findings demonstrate that a multi-pronged approach that entails several geospatial methods including cloud computing techniques such as GEE is important in accurate detailed soil erosion risk modelling. The RF classification of Analysis ready Sentinel 2 images successfully mapped the LULC clearly depicting the soil erosion hotspots in the Shashe and Tugwi –Zibagwe sub-catchments. The area under cultivation has been increasing at the expense of other land covers for instance grasslands and woodlands in both sub-catchments which exposes the areas to varying levels of erosion. Soil loss was considerably high in areas under cultivation when compared to other land covers in the respective areas. Results show that, the lowest risk of erosion was 15 t ha^{-1} $year^{-1}$ with the highest being 150 t ha^{-1} $year^{-1}$, for the Shashe sub-catchment. Soil erosion risk tends to be highly concerted in the north-eastern parts of the Shashe sub-catchment and along drainage networks. Comparatively, the Tugwi–Zibagwe had considerable high erosion risk on the central and southern parts mainly around agricultural fields in communal areas. In the Tugwi–Zibagwe sub-catchments the lowest and risk of erosion was 11 t ha^{-1} $year^{-1}$ and the highest over 100 t ha^{-1} $year^{-1}$. Therefore, the increased soil erosion rates resulted in declining soil fertility. The inherent impact is reduced productivity yet; agriculture is the main livelihood strategy.

CRediT authorship contribution statement

Tatenda Musasa: Writing – original draft, Methodology, Data curation, Conceptualization. **Cletah Shoko:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Thomas Marambanyika:** Writing – review & editing, Supervision, Data curation. **Timothy Dube:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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