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Abstract:
Soil loss and its geostatistical analysis was studied at the kebele level in Tigray. The method applied to estimate soil loss was the revised universal soil loss equation. Earth Engine's public data archive was used for data collection. The R-factor was developed from the SM2RAIN-ASCAT (2007-2021) global daily satellite rainfall data, the K-factor was developed from USDA-3A1A1A_M/v02 soil data, the C-factor was derived from MODIS/006/MOD13A2, and LS factor was derived from WWF Hydro SHEDS Hydrologically Conditioned DEM. By integrating all factor, the soil loss was obtained by the RUSLE model. Spatial Autocorrelation (Morans I) statistic was used to identify the pattern of soil loss and Ordinary Least Squares (OLS) linear regression was used to model a soil loss in terms of its relationships to R, K, LS, C, and P factors. The grouping analysis tool was used to Group kebele based on soil loss. The results indicate that the estimated average soil erosion is 82760 t ha^{-1} y^{-1}. The pattern of soil loss at the kebele level was found highly clustered with a z-score of 23.39. The groping analysis tool divides the kebele into five categories to identify the cause of spatial variation of the soil loss in Tigray. Groups 1, 4 & 5 were found as in the outlier positions due to the high LS factor. The results deliver valuable information for decision-makers and planners to take suitable land administration measures to minimize the soil loss. It, therefore, indicates google earth engine is a significant platform to analyze the RUSLE model for evaluating and mapping soil erosion quantitatively and spatially.

Keywords: RUSLE, GEE, Soil Erosion, OLS, Grouping Analysis.

Introduction

Land degradation hinders people across the globe from ensuring food security. Around 1.05 billion people are currently food insecure (Kuria et al. 2018). This phenomena is likely to get worse with this trend of land degradation with the world's population expected to rich 9 billion by 2050 (Rockström and Falkenmark, 2015). It is caused by many factors of both natural and anthropogenetic sources. Deforestation and soil erosion are among the major reasons for land degradation. while deforestation is caused by increased population and the subsequent need for agricultural expansion, Soil erosion is caused by runoff (more than 90% is caused by water erosion) (Megerssa and Bekere 2019). The effects of land degradation might not be revealed over a short period; it is however manifested gradually with a catastrophic drought and starvation (Tesfahunegn 2020).

Soil erosion has continuously been an issue for human creatures all through history (Demirci & Karaburun, 2012). Soil erosion by water is a serious global problem. Around 5Mg ha-1 of beneficial topsoil is misplaced in lakes and seas each year (Angima et al., 2003). Land degradation is a serious problem across Sub-Saharan Africa. more than sixty-five percent of the land is degraded up to some extent from very low to high. (Sileshi et al., 2019). So, a Precise evaluation of soil loss caused by precipitation is basic for common and rural assets administration (CHEN et al., 2017). Evaluation of soil disintegration is valuable in arranging and preservation works in a basin or a region (Ganasri & Ramesh, 2016).

Ethiopia, a country is mostly hit by land deterioration that resulted in poverty, reduction in agricultural yield, food insecurity, loss of human life, loss of livestock, etc. Around two billion tons of soil are eroded annually which is equivalent to the loss of about 1 million tons of grains annually (Megerssa and Bekere 2019). Soil erosion has a direct effect on yield reduction of agricultural products by altering the physical-chemical properties of soil such as a change in soil organic matter, texture, soil water content, soil nutrient decline, etc, which are all determining factors for the growth of crops. Consequences of Soil erosion vary from nutrient losses at the upper stream to sedimentation deposition downstream, declining soil fertility, and yield losses.

Soil erosion in Ethiopia is more common in the highlands (semi-arid areas) when compared to the low lands which receive relatively adequate rainfall amounts. Semi-arid areas are with low vegetation cover, high runoff & soil loss. Soil erosion rates are generally highly dependent on land use type and agro-climatic zones. For instance, cultivated lands encounter a higher erosion rate than grasslands. The Tigray region in northern Ethiopia is highlands that are severely prone to soil erosion. The main reason is associated with mountainous topography, intense rainfall, and lack of /little vegetation cover. Frequent soil erosion in the Tigray has occurred for decades which made farming on old arable lands difficult and farmers had to look for more marginal lands (Esser and Haile 2002).

Soil erosion is because of runoff produced during the summer's short but intense rainfall in Tigray. Other activities that aggravate soil erosion are the clearing of forests for the sake of alternative fuel sources. In Tigray, only the urban areas that account for 15% of its population have access to power. The rest 85% living in remote areas are deprived to energy and all they depend is on wood fuel. Besides, cow dungs and cover crops that are vital to soil fertility are again used as fuel source. This has a detrimental effect on the quality of soil. Expansion of cultivated land by clearing forests has degraded the condition of the soil and accelerated soil erosion. The hilly and steep slope areas in the region are the most vulnerable to erosion because of the topography, old farming techniques of conventional tillage, and over cultivation (Kaygusuz, 2011).

Most of researches conducted so far focus on mitigating soil erosion mainly on implementation of soil and water conservation programs (Biazin et al. 2012), integrated watershed management (Teka et al. 2020), water harvesting (Filho and de Trincheria Gomez 2017; Nyssen et al. 2010), and conservation tillage (Zerssa et al. 2021) etc. this programs are meant to enhance food and cash production, improve soil fertility and improve small holder farming. Those programs have been implemented at both house hold and community level. Those measures, although are limited to only few areas in the region such as the case of Abraha we atsbeha have shown promising results (Tadesse, Gebrelibanos, and Geberehiwot 2016). Soil and water conservation programs have the capacity to reverse erosion by reducing slope length, building a small retention basin to accumulate sediment and runoff, reducing water overland flow or water erosion (Vancampenhout et al. 2006).

However research on the estimation of soil losses at regional or zonal level is very limited or insignifant. Despite being very limited, research conducted on soil loss estimation are conducted at plot scale and thus might not be used for estimating soil loss for large areas. Govers and Moeyersons (2005), conducted research on soil loss estimation at a plot scale on stone bunds which are commonly applied soil conservation technique by comparing plots with and without stone bunds. They found that mean annual soil loss estimated from sheet and rill erosion was 57 ton/ha/yr. no research has been conducted for estimating soil loss for a larger areas at wereda level (the second administration unit in the region). Another study conducted on exclosure areas.

Estimating the rate of soil erosion for a larger areas is however very essential element that should have been prioritized before the implementation of soil conservation works. It helps to quantify the amount of soil lost and the resulting decline in economy both at regional and country level. 2 billions of soil loss is equivalent to a loss of about 1 million ton of grains. Assessment of soil erosion at wider scale can help on the planning and design of agricultural policy and strategies in the region. It can help categorize areas from the most degraded areas to areas with less erosion hence, to identify areas of focus. And thus answers the question which areas need to be prioritized during soil conservation programs. This can facilitate the implementation and adoption more soil conservation works.

Soil erosion models play a key role at forecasting the impacts of landscape alterations on both socio economic and environmental sustainability. They help estimate soil loss and runoff from different landuse, gives information about the present and future erosion and scenario analysis. They also serve as a guideline for policies and strategies linked to soil water conservation.

There exist several erosion models have been developed so far including the RUSLE model (revised universal soil loss equation), soil & water assessment tool (SWAT), AGNPS (Agricultural non-point source pollution), Euro SEM (European soil erosion model), WEPP (water erosion predication project) etc. all with a common goal of sediment or soil loss estimation but mostly differ on the input parameters, whether an empirical, conceptual or physical based models are used for simulating the model, process and complexity of the model etc(Moges and Bhat 2017). The selection on a suitable model is highly dependent on the aim of the study, catchment properties, data availability, model accuracy and simplicity (Luvai, Obiero, and Omuto 2022).For instance, RUSLE, is a commonly applied empirical soil erosion model designed for areas with hilly topography.Empriclal models such as RUSLE are an easy to use models which can even be applied in case of limited input data(P.U. et al. 2017). It has been applied by (Bagegnehu, Alemayehu, and Nigatu 2019; Ganasri and Ramesh 2016; K., F., and O. 2020; Mekuria et al. 2009; Moges and Bhat 2017). The USLE model that was developed by Wischmeier and Smith, (1978) was first designed to estimate soil loss for sloppy areas where parameters like slope length and slope steepness were used to determine the impact of terrains on erosion. This model was later on improved to a RUSLE model which made it applicable for more land use types such as crop land, range lands, forest lands, and steep areas (P.U. et al. 2017; Van Remortel, Hamilton, and Hickey 2001). The RUSLE model have been applied enormously for the last 20 year and continued to be the most preferred soil erosion model used to estimate sheet & rill erosion caused by runoff (Borrelli, Alewell, and Alvarez 2021).

Nowadays, including remote sensing in to existing soil loss modeling has become a popular technique in areas of hydrology, agriculture, soil science etc for simulating events and processes with the help of spatial analysis (Ahmed Harb Rabia 2012). Gis based water erosion model can help examine spatial pattern of soil attrition, its transfer and deposition as well as its effect on the landscape formation(Mitasova et al. 2013). Combination soil erosion models, with remote sensing data such can identify highly erosive areas on a cell by cell basis with input from digital elevation model(Ganasri and Ramesh 2016). .

Erosion models, depending on the catchment scale for which they are designed need different spatial dataset resolutions. For instance, a spatial resolution up sub meter is needed for hill slope scale where sheet and rill erosion is dominant. A watershed/catchment scale model on the other hand requires a spatial resolution of up to 10 meter and includes large gullies. Regional scale modeling are macroscale catchments of up to thousands of km2, thus require a spatial resolution from 30 meter to hundred meters(Mitasova et al. 2013). Some of the papers that combined GIS and one of the RUSLE erosion models (Ahmed Harb Rabia 2012; Bagegnehu et al. 2019; Borrelli et al. 2021; K. et al. 2020; Luvai et al. 2022; Moges and Bhat 2017).

The USLE (Wischmeir & Smith, 1965, 1978) was formulated to predict the long term twenty years mean soil loss per year from field size areas using five factors focusing on the effect of climate, especially rainfall, soil, topography, cropping, and soil conservation activities (Kinnell, 2014). The RUSLE has also expanded its uses to different conditions (Lu & others., 2004). RUSLE is one of the most widely used (Abu Hammad & others., 2004) soil erosion models worldwide (Tanyaş et al., 2015).

The rainwater erosivity factor denotes the kinetic energy of raindrops which could affect the steadiness of soil aggregates (Yue et al., 2020) and enhance soil loss (Hateffard et al., 2021). The soil erodibility calculate k appears the resistance of soil against disintegration due to the effect of a raindrop and the rate and sum of runoff created for that precipitation impact, under a standard condition (Ghosal & Das Bhattacharya, 2020). Climate change could further accelerate the process of soil loss, in consequence of climate change, an increase in local flash floods and soil erosion intensity would be expected (Fiener & others., 2013). As the temporal resolution of precipitation measurement declines calculated precipitation erosivity declines (Yue et al., 2020).

The soil erodibility variables for showing soil erosion are stated as the k variable in the widely used soil erosion model the USLE and its revised version RUSLE (Panagos et al., 2014). The soil erodibility variable (K) denotes the power of soil against disintegration because of the effect of the drop of the rain and the rate and amount of run-off developed for that precipitation effect, under a standard condition (Ghosal & Das Bhattacharya, 2020). The utmost problem with soil erosion modeling at greater spatial scales is the absence of data on soil characteristics.

When utilizing the USLE or RUSLE, the impacts of terrain on soil disintegration are evaluated by the steepness & length of the slope constituents of the dimensionless LS factor, where LS is one of five variables (R, K, LS, C, and P) that are multiplied all to calculate the normal yearly soil removal per unit area (Van Remortel et al., 2001). The LS figure contains the slope length figure (L) and the slope factor (S). It is broadly accepted that slope length is the more tricky portion. The improvement of GIS permits for programmed extraction of slope length from high-resolution DEMs, hence an inefficient manual process is avoided (Liu et al., 2015). The LS-factor was initially created for slopes less than 50% slant and has not been tried for more extreme slopes. To overcome this confinement, (Schmidt et al., 2019) adjusted both components slant length L and slant steepness S for conditions tentatively watched at Swiss elevated prairies.

Greenery cover is seen among the foremost critical saving measures for controlling soil disintegration caused by rainfall. a lot of work has been published related to the fact that vegetation cover is more sensitive, down to earth, it is possible to calculate normalized difference vegetation list (NDVI) for calculating ''cover management (C) factor'' within the Changed Universal Soil Loss Condition (RUSLE), the foremost commonly recognized soil disintegration prediction show around the world (Vatandaslar & Yavuz, 2017). Land cover, a vital calculation for checking changes in land use and disintegration chance, has been broadly checked and assessed by vegetation indices (Durigon et al., 2014).

The conservation practice variable (P) of the RUSLE stays to a great extent hazy (Tian et al., 2021). The variables utilized in these models were ordinarily assessed or calculated from field estimations. The strategies of evaluating soil misfortune based on disintegration plots have numerous confinements in terms of fetched, representativeness, and unwavering quality of the coming about information. They cannot give the spatial distribution of soil disintegration loss due to the limitation of constrained tests in complex situations. So, mapping soil disintegration in large zones is regularly exceptionally troublesome utilizing these conventional strategies (Lu et al., 2004). In any case, the utilization of farther detecting and geographical information framework (GIS) procedures makes soil disintegration estimation and its spatial dispersion attainable with reasonable costs and way better precision in bigger zones. The RUSLE has been adopted in a Geographical data information system (Kouli et al., 2009). Spatial analysis is a part of geography, which has a varied and inclusive ability that comprises the basic visual investigation of maps and imagery, computational analysis of areal patterns, finding best routes, point selection, and advanced forecast modeling(ESRI, 2013).

GIS is included in many disciplines have been used significantly in combinations of many different models, such as RUSLE, to predict soil disintegration (Demirci & Karaburun, 2012). Spatial statistics were somehow developed by Pearson and Fisher, but their modern appearance is mainly due to Whittle, Moran, and Geary (Waters, 2012).

Using GIS models any one can forecast soil removal risk, based on the level of erosion at a variety of levels (Evans & Boardman, 2016), but field-based assessments are very important for result validation. As we know the population is increasing day by day so the protection of soil has been a very significant task (CHEN et al., 2017).

The Geographers and GIS experts focus on the need of the land administrators and policy developers and they are more concerned with the spatial variation of soil removal risk than only numerical figures of soil erosion loss (Lu & others, 2004).

This research focuses on application of geostatistical analysis for estimating soil loss for Tigray. It is done by combining GIS data with the revised universal soil loss equation model (RUSLE).

Purpose of the work

First, to estimate the soil erosion using RUSLE; second, to predict the pattern of soil loss at the kebele level in Tigray Region; third, to exercise linear regression to understand the impact of variables of soil loss and the last to group the kebele based on soil loss estimation.

There have been relatively few regional studies in the Tigray regional state of Ethiopia on the use of RUSLE technologies for finding the kebele prone to more water erosion. Using Geostatistics, the current study tried to analyze the areal differentiation of soil loss due to rainfall in the study area.

2. Material and Methods

2.1 Study Area

This study was conducted at the kebele level in Tigray (Fig. 1). The Tigray region is one of the ten regions in Ethiopia. It is situated at (12^0 15’ -$14^0$50’) N & ($36^0$27’-$39^0$59’) E, northern tip of the country. It has an altitude ranging from 500 m to 4000 m.a.s.l. It is bordered with the Amhara region, Afar region, Sudan and Eritrea in the south, east, west and north directions respectively. With total area of 80 Km2, the region is known for its rough topography and hilly slopes (Balehegn et al., 2019). It has semiarid agroecology with short summer and long winter, annual precipitation (200-100 mm) and average temperature of 18 0C, and an altitude ranging from 500 m to 4000 m.a.s.l (Fitsum et al., 2000). The region has seven “zones” (first administration unit) and 52 districts and 763 kebelles (smallest administration unit) (Beyene et al., 2021; Rabia, 2012). Several land use types including forests, croplands, builtup area, and exclosure areas exist in Tigray. Typical soil types in the region include, lithosols, cambisols, acrisols, vertisols luvisols, xerosols regosols, arenosols, fluvisols rendzinas nitosols

(Gebreegziabher et al., 2009). The population in Tigray is estimated as 4.4million with 3% annual growth which was estimated by CSA, 2010 (Balehegn et al., 2019)..Mixed farming system of crop farming with livestock production are typical farming practices in the region of which more than 90% of farming is practiced by small holder farming.(Zerssa et al., 2021).

2.2 Workflow

RUSLE is fit for the soil loss estimation model that can be used at any level of region (Ganasri & Ramesh, 2016). The workflow implemented in this study is given in fig. 2.

2.3 Data Used

The source and type of data used are given in table 01.

2.4 Data Processing

2.4.1 RUSLE

RUSLE, one of the foremost widely-used models (Eq. 1), gives an idea of how to get the interaction between precipitation and soil erosion (Xu et al., 2013).

$$A = R * K * LS * C * P \qquad (1)$$

where, R stands for precipitation runoff erosivity factor (MJ·mm·km−2·h−1·month−1); K is for the soil erodibility variable (t·km2·h·km−2 MJ−1·mm−1); LS is steepness and length of the slope factor (dimensionless); C is the factor for cover management (dimensionless); P is the erosion control practice factor (dimensionless, between 0 and 1) and A is the calculated soil loss (t·km−2·annum−1).

To calculate soil loss for Tigray region of Ethiopia using Google Earth Engine, Revised Universal Soil Loss Equation (RUSLE) model was used. Here is an code that that was used given below (Box 1):

```
// Load the Tigray region boundary
var tigray = ee.FeatureCollection('users/yourUsername/tigrayBoundary');
// Load the necessary datasets
var srtm = ee.Image('USGS/SRTMGL1_003');
var ls8 = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR');
var soil = ee.Image('OpenLandMap/SOL/SOL_CLAY-WFRACTION_USDA-
3A1A1A_M/v02');
var landCover = ee.Image('MODIS/006/MCD12Q1/051');
// Define the RUSLE parameters
var rainfallFactor = ee.Image.constant(1);
var soilErosionFactor = soil.select('b0').multiply(0.001);
var slopeFactor =
srtm.select('elevation').multiply(0.1).atan().multiply(0.0573).sin().pow(1.3);
var landCoverFactor =
ee.Image(landCover.select('LC_Type1').eq(12)).multiply(0.5).add(ee.Image(landCo
ver.select('LC_Type1').eq(14)).multiply(0.2)).add(ee.Image(landCover.select('LC_T
ype1').eq(20)).multiply(0.3));
// Calculate the RUSLE factors
var rusleFactors = ee.ImageCollection.fromImages([
  rainfallFactor,
  soilErosionFactor,
  slopeFactor,
  landCoverFactor
]).reduce(ee.Reducer.product());
// Load the daily precipitation dataset
var precipitation = ee.ImageCollection('UCSB-CHG/CHIRPS/DAILY')
  .filterDate('2019-01-01', '2019-12-31')
  .select('precipitation');
// Calculate the average annual precipitation
var annualPrecipitation = precipitation.mean();
// Calculate the RUSLE model
var rusle = rusleFactors.multiply(annualPrecipitation).reduce(ee.Reducer.sum());
// Mask the RUSLE result using the Tigray boundary
var rusleMasked = rusle.updateMask(tigray);
```

Box 1 GEE Code

In this code, necessary datasets such as the digital elevation model (SRTM), Landsat imagery, soil data, land cover data, and precipitation data was loaded. Then we defined the RUSLE parameters such as the rainfall factor, soil erosion factor, slope factor, and land cover factor. We calculate the RUSLE factors and apply them to the precipitation data to get the soil loss result. Finally, we mask the result using the Tigray boundary.

2.4.2 Geostatistical Analysis

To predict the pattern of soil loss at kebele level in Tigray the Spatial Autocorrelation (Global Moran's I) tool was used. The Moran's I statistic is a measure of spatial autocorrelation, which quantifies the degree of similarity between the values of a variable at different locations in a spatial dataset. The formula for Moran's I statistic is:

I = (n / W) * (ΣΣwij * (xi - x̄) * (xj - x̄)) / (Σ(xi - x̄)^2) (2)

where:

- n is the number of spatial units in the dataset
- W is the spatial weights matrix,
- wij is the weight between unit i and j in the spatial weights matrix
- xi is the value of the variable at unit i
- x̄ is the mean value of the variable across all units

The numerator of the formula calculates the sum of the products of the deviations of the variable values from the mean, weighted by the spatial relationships between the units. The denominator calculates the sum of the squared deviations of the variable values from the mean. The resulting value of Moran's I statistic ranges between -1 and 1, where negative values indicate negative spatial autocorrelation (i.e., dissimilar values are clustered together), positive values indicate positive spatial autocorrelation (i.e., similar values are clustered together), and values close to zero indicate spatial randomness.

To meet the third research objective ordinary least squire regression type was used (Eq. 2).

$$\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots \beta_n X_n + \varepsilon \qquad (3)$$

Where γ is the dependent variable, β is coefficients, X is explanatory variables and ε is the random error.

To better understand how the factors are affecting the soil loss predictions Grouping Analysis tool was used to classify the kebele of Tigray (Eq. 3 & 4).

$$\text{Calinski} - \text{Harabasz pseudo F} - \text{statistic} = (R^2/n_c - 1)/(1 - R^2/n - n_c) \qquad (4)$$

Where:

$$R^2 = \frac{SST - SSE}{\text{SST}} \qquad (5)$$

3. Results

3.1 Precipitation runoff erosivity factor (R)

The predicted map of the annual R factor is given in Fig. 3.1. The min. and max. R is found 116 to 8889 respectively. The mean annual R in Tigray is 3122 with a standard deviation of 1272.

3.2 Soil erodibility factor (K)

The predicted map of the annual R factor is given in Fig. 3.2. The min. and max. K is found at 0.21 to 0.37 respectively. The mean annual K in Tigray is 2.3 with a standard deviation of 0.01.

3.3 Slope length steepness factor (LS)

The predicted map of the annual LS factor is given in Fig. 3.3. The min. and max. LS is found 00 to 1258539 respectively. The mean annual K in Tigray is 3031 with a standard deviation of 16409.

3.4 Cover management factor (C).

The predicted map of the annual C factor is given in Fig. 3.4. The min. and max. C is found at 0.013 to 0.052 respectively. The mean annual C in Tigray was found 0.04.

3.5 Annual Soil Loss

The estimated soil loss in Tigray is shown in Fig.04. The min. and max. soil loss is found 00 to 30457865 t ha-1 year -1 respectively. The mean annual K in Tigray is 3031 t ha-1 year -1 with a standard deviation of 16409.

3.6 Pattern of Soil loss at the kebele level

The result of autocorrelation for pattern analysis is given in table 02 & Fig. 05, which, indicates soil loss at the kebele level is highly clustered (z = 23.39).

3.7 Standard Residuals of Annual soil loss Prediction

Fig. 06 & 07 shows the map and histogram of Standard Residuals respectively. Table 03 & 04 shows the results of the model variables & OLS diagnostics. The multiple R2 (0.92) was obtained from the ordinary least squared (OLS) regression model.

3.8 Groups of Annual soil loss Prediction

Figure 08 & 09 shows the map of the groups of Annual soil loss Prediction & Parallel box plot chart respectively. Group numbers one, four, and five are of special interest because of their outlier positions as shown in the Parallel box plot chart (Fig.10).

Discussion

The Tigray region in northern Ethiopia has been experiencing severe soil erosion over the past few decades. This is due to a combination of factors, including deforestation, overgrazing, unsustainable land use practices, and extreme weather events such as droughts and floods. However, very less work is done on soil erosion in Tigray based on GIS. Estimates of soil removal by water show significant variation at the kebele level, this variation is a result of the variation in the distribution of different types of the soil, high flow accumulation, variations in vegetation cover, and finally spatial variation of rainfall. The R factor; which shows the impact of rainfall was calculated based on reliable rainfall data with quality control. Data record provides better information, especially in Africa (Brocca & others 2019). The K factor that is modeled in this study is also based on the full soil properties currently available. The same soil data was used by other researchers such as Viscarra, E. N., & Baldock, J. A. in 2014. de Brogniez, D., Ballabio, C., Stevens, A., Jones, Montanarella, L., & van Wesemael, B. in 2015. The results are consistent with other scholars. Most areas of Tigray have a relatively small value of K. The vegetation data MOD13A2 used to calculate cover management was collected from the Google Earth engine archive. The same data has

also been used by He et al., 2022; Wu et al., 2022; Chabot et al., 2022; He & others, 2022. The results were validated and published.
The OLS regression model was used to predict the significance of the factors; different tests are required to confirm the reliability of the OLS regression model. The modeled relationships are consistent because obtained statistic of Koenker is not statistically significant (p more than 0.005). The residuals show a Gaussian spatial pattern by the areal autocorrelation (Global Moran's I) analysis. model predictions are unbiased because the Jarque-Bera Statistic test is also not statistically significant (p more than 0.01). There are no high intercorrelations among explanatory variables because the Variance inflation factor (VIF) values of the OLS range between 1.03 and 1.5.
In the result of the grouping analysis Group, four have maximum mean soil loss, and this is primarily due to the high LS factor. The high soil loss in group one is due to less vegetation and more rainfall. Soil loss in Group five is also like group one and it is due to the High LS factor.

Conclusion

Smart techniques such as the GEE interface were used for erosion factors of R and K. In general, it was found that the soil erosion is high due to zig-zag topography in the Tigray region, which equates to heavy annual soil losses over this area. The kebele that suffers from severe soil erosion occurs in areas having higher slope length and steepness (LS) factors; therefore, these areas should be further studied. GEE is useful for the estimation of soil removal. As it can process data input at any level, RUSLE can provide quantitative estimates of long-term soil removal in Tigray. To address soil erosion in Tigray, a number of strategies should be implemented, including reforestation programs, terracing to prevent gully erosion, improved irrigation practices, and the use of sustainable farming techniques such as conservation agriculture.

Declarations

Competing interests

We wish to confirm that there are no conflicts of interest associated with this publication. The researchers declare that this work follows the standards of a genuine research study.

Authors' contributions

Zubairul Islam contributed in GIS analysis part, Fikre Belay made the figures, Tadesse Brhane Hadgu compiled the background of the study, Haftom Teshale contributed in data analysis, Yalembrhan Debebe also helped in data analysis. All the researchers are well informed related to all the content given in the manuscript.

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Availability of data and materials

The data used can be collected from the data source section given in the manuscript.

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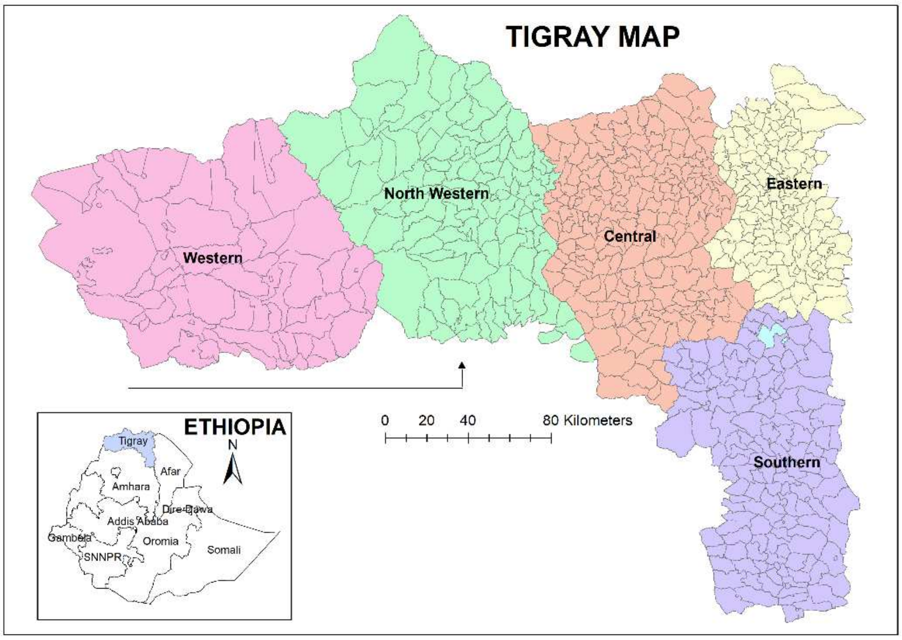

Figure 1 Study Area Map

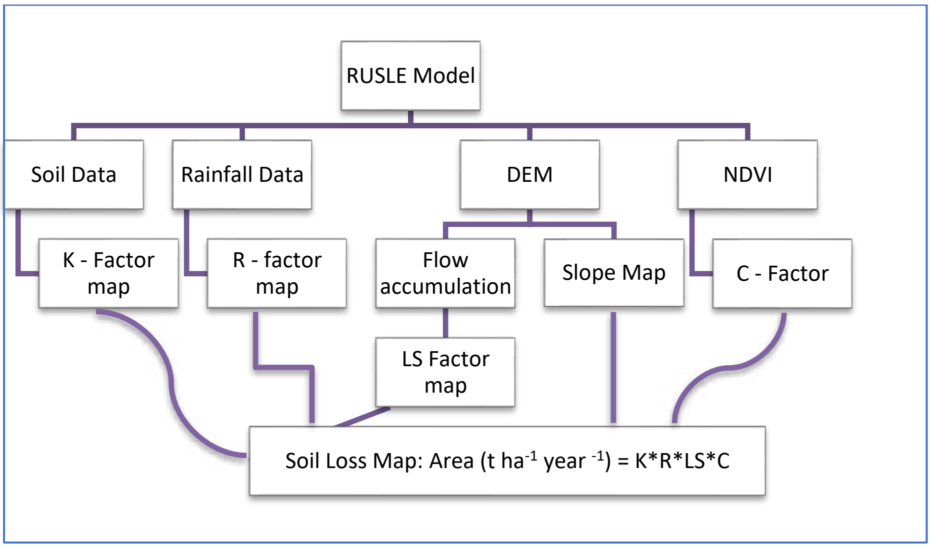

Figure 2 RUSLE Workflow chart

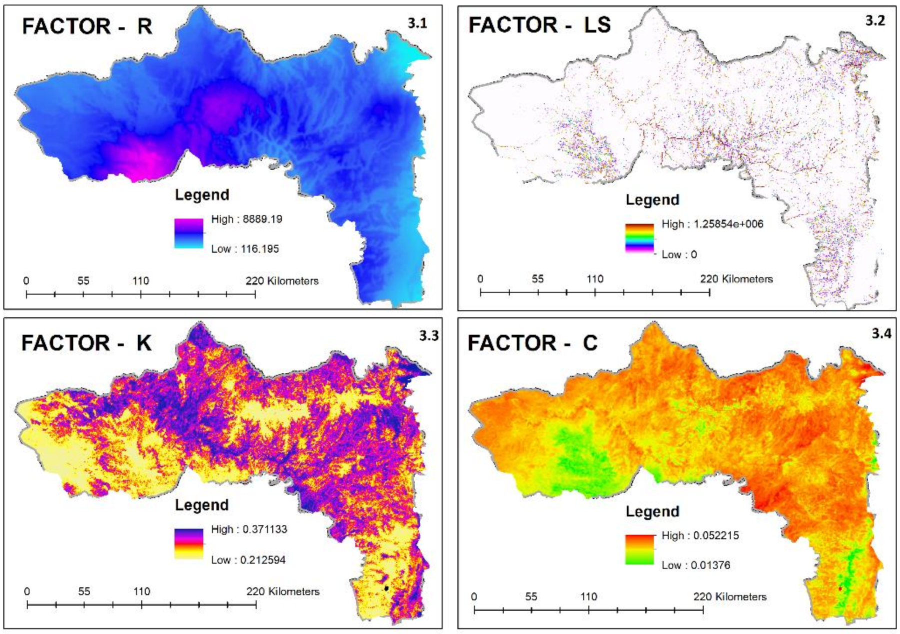

Figure 3 Erosivity factors

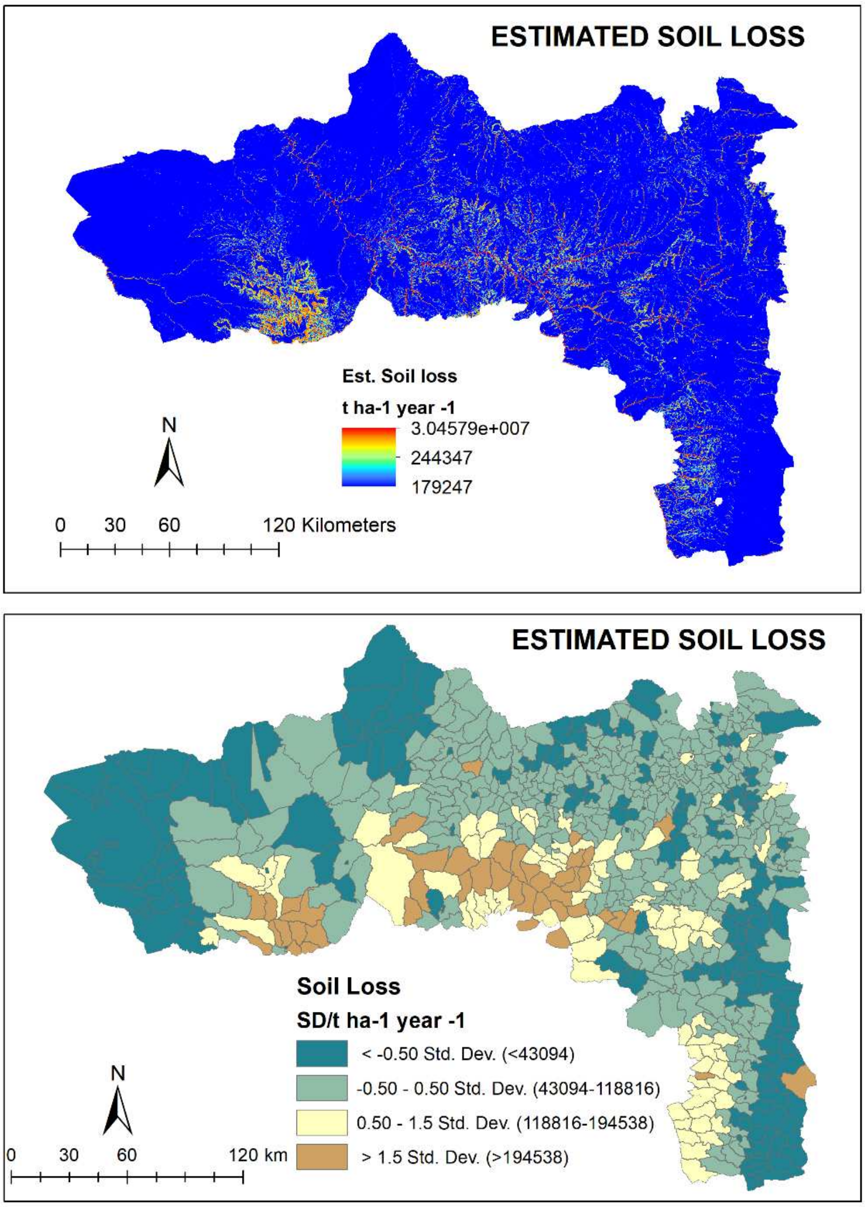

Figure 4 Estimated Annual soil erosion

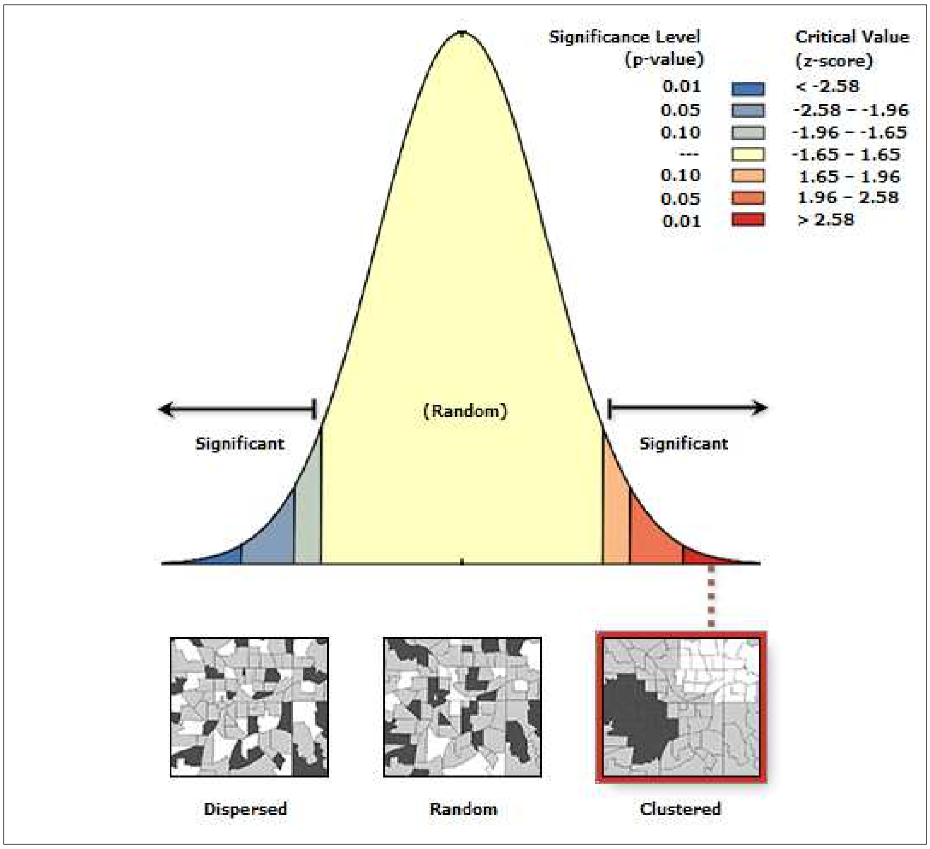

Figure 5 Pattern at Kebele level

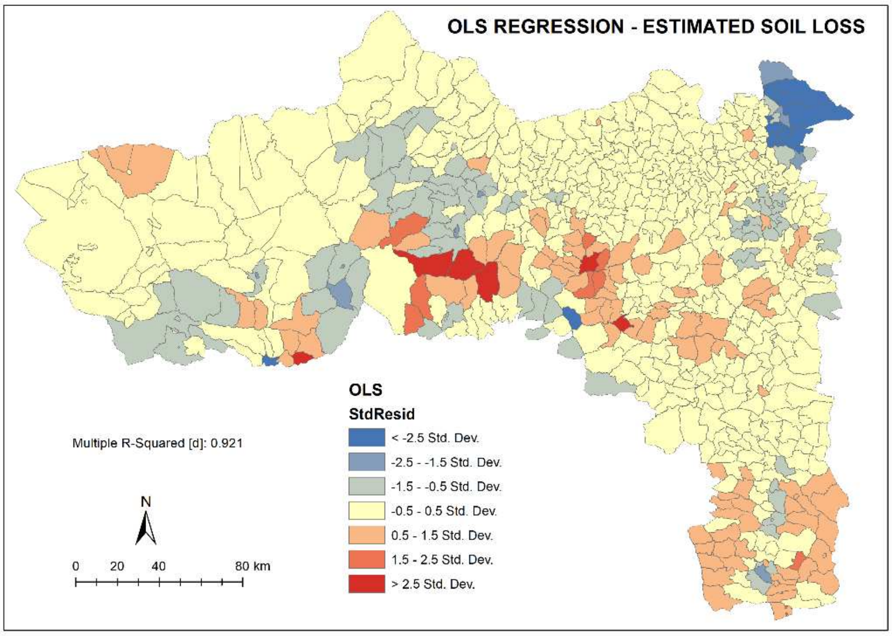

Figure 6 Standard Residual Map

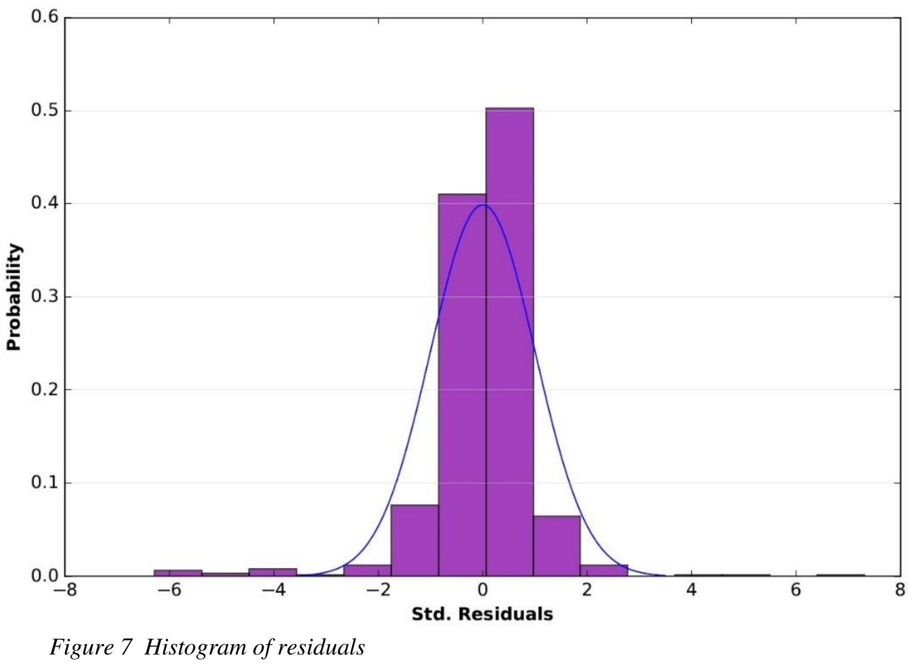

Figure 7 Histogram of residuals

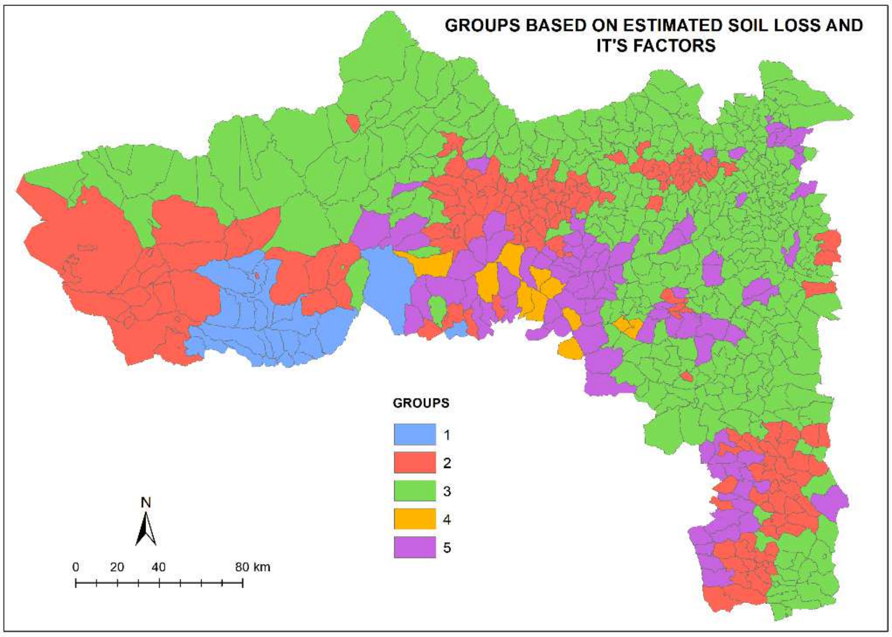

Figure 8 Groups of Annual soil loss Prediction

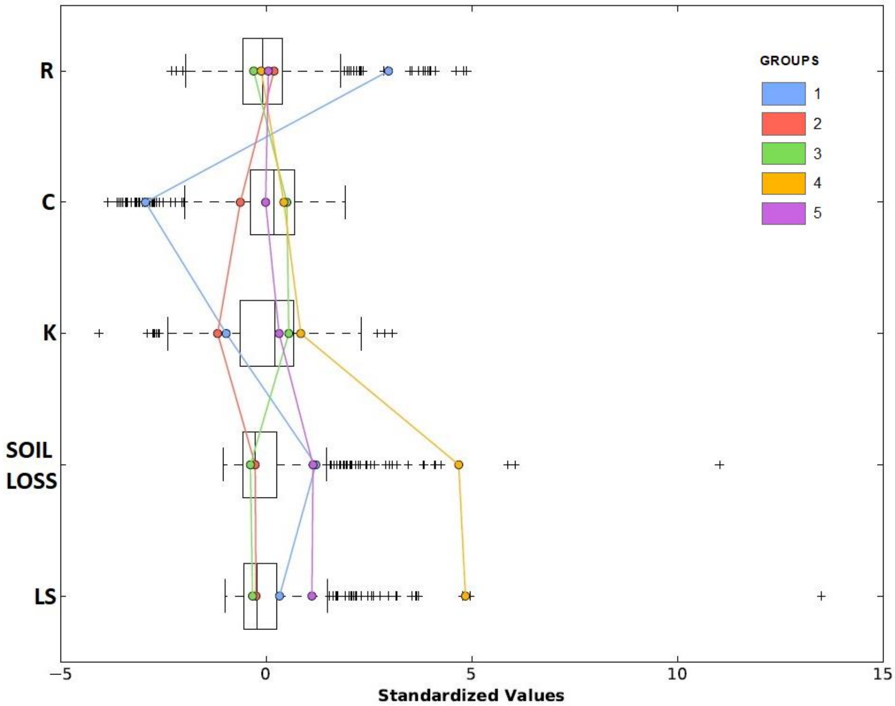

Figure 9 Parallel Box Plot

Group	Mean	Std. Dev.	Min	Max	Share
1	172361.8247	76910.7136	19763.4227	370029.0830	0.3833
2	60709.9317	35035.8486	3463.6037	153965.4272	0.1647
3	51895.9119	28022.0837	1788.7930	128363.9883	0.1385
4	435496.7121	170652.2986	281000.4397	915630.9149	0.6945
5	167187.1231	46755.4050	75232.8590	312910.9224	0.2601
Total	80955.0861	75722.1535	1788.7930	915630.9149	1.0000

Figure 10 Groups based on mean soil loss

Table 01 Data Types and sources

Dataset	Content	Format	Data Source
Precipitation	Monthly Rainfall in mm, one km spatial resolution, Covering Period 2007-2018.	tif	https://openlandmap.org/ (Brocca et al., 2019)
Soil	Sand, Silt, Clay, Organic Content	tif	https://openlandmap.org/
DEM	SRTM dataset with 1 km spatial resolution	tif	https://www.hydrosheds.org/
NDVI	The MODIS vegetation index (VI) products.	tif	https://lpdaac.usgs.gov/
Basic geographical information	Administrative Map	Vector	https://www.diva-gis.org/gdata

Table 02 Global Moran's I Summary

Moran's Index:	0.295482
Expected Index:	-0.001508
Variance:	0.000161
z-score:	23.394051
p-value:	0.000000

Table 03 OLS Results - Model Variables

Variable	Coefficient	Std Error	t-Statistic	Probability [b]	Robust SE	Robust t	Robust Pr	VIF
Intercept	-134132.2	30524.5	-4.394	0.000016*	35446.6	-3.8	0.000179*	----
R Factor	25.0	0.8	31.354	0.000000*	1.4	17.7	0.000000*	1.18
LS Factor	24.2	0.3	81.610	0.000000*	0.9	26.8	0.000000*	1.05
C Factor	1323258.1	330819.5	4.000	0.000078*	391012.4	3.4	0.000771*	1.51
K Factor	67384.7	127095.2	0.530	0.6	162287.6	0.4	0.678	1.38

Table 04 OLS Diagnostics

Input Features:	Tigray Kebele	Dependent Variable:	Est. Soil Loss Mean
No. of Observations:	664	Akaike's Information Criterion (AICc)	15129.52
Multiple R-Squared:	0.921162	Adjusted R-Squared	0.920684
Joint F-Statistic:	1924.987744	Prob(>F), (4659)	0.000000*
Joint Wald Statistic:	1110.127098	Prob(>chi-squared), (4)	0.000000*
Koenker (BP) Statistic:	128.428958	Prob(>chi-squared), (4)	0.000000*
Jarque-Bera Statistic:	6587.612506	Prob(>chi-squared), (2)	0.000000*