SWAT model-based quantification of the impact of land use change on sediment yield in the Fincha watershed, Ethiopia

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Abstract

In recent years, Ethiopia is facing problems due to soil erosion, mainly because of the conversion of natural vegetation cover into cultivated land. Soil erosion is also affecting dam reservoirs, which are threatened by an increase in sediment yield entering the lake. The present study focuses on the Ethiopian Fincha watershed and takes advantage of the potentiality of SWAT, to investigate how land use land cover changes impact soil erosion and the consequent sediment yield entering the Fincha Dam, eventually suggesting potential management strategies. The SWAT model was calibrated and validated using time series data of stream flow and sediment from 1986 – 2008 years, and its performance was evaluated by looking at the coefficient of determination, Nash-Sutcliffe simulation efficiency, and per cent bias. Once validated, the SWAT model was applied to derive sediment yield for the future thirty years, based on forecasted land use land cover conditions. The results show that the mean annual soil loss rate increased from 32.51 t ha^{-1} in 1989 to 34.05 t ha^{-1} in 2004, reaching 41.20 t ha^{-1} in 2019. For the future, a higher erosion risk should be expected, with the annual soil loss rate forecasted to be 46.20 t ha^{-1} in 2030, 51.19 t ha^{-1} in 2040, and 53.98 t ha^{-1} in 2050. This soil erosion means that sediments transported to the Fincha Dam, located at the watershed outlet, increased significantly in the last thirty years (from 1.44 in 1989 to 2.75 mil t in 2019) and will have the same trend in the future (3.08 to 4.42 mil t in 2019 and 2050, respectively), therefore highly affecting the Fincha reservoir services in terms of reduction of water volume for irrigation and hydroelectric power generation.

Keywords

Ethiopia; Fincha watershed; land use land cover; sediment yield; SWAT

1. Introduction

Changes in land use land cover (LULC) can cause soil erosion, which eventually contributes to increasing the quantity of sediments entering waterbodies and dam reservoirs. This process is evident in arid and semi-arid environments (Sharma et al., 2022), where soil degradation can generate cascading effects like poor conditions and famine (Yesuf et al., 2015). To counteract the erosion process and guarantee suitable development, effective management strategies and policies, and implementation of best management practices with the active involvement of all stakeholders are needed. However, to adopt adequate soil conservation measures, the extent and rate of soil erosion, as well as the causes of land degradation, must be assessed via the most appropriate modelling approach.

Nowadays, the Ethiopian economy and population are taking advantage of the presence of multiple dams and reservoirs, providing the availability of a large amount of water resources and suitable topography (Assfaw, 2019). However, these reservoirs are highly impacted by soil erosion, with consequent severe problems of sedimentation even beyond their dead storage capacity, which is a clear sign of poor land use practices and improper land management. Many studies pointed out that capacity to inflow ratio, amount of sediment flowing into the water, size and texture of the sediment, basin trap efficiency, reservoir operation methods, nature of the soil in the catchment area, basin topography, land use and vegetation cover in the catchment area and rainfall intensity are the main causes for sedimentation (Kumar et al., 2012; Foteh et al., 2018; Ivanoski et al., 2019). The reduction of storage volume due to sedimentation negatively impacts the capacity to produce hydroelectric power, increasing production and maintenance costs, reducing the availability of water for concurrent uses like irrigation, and eventually shortening the reservoir life.

Past investigations have shown a large variety of hydrological models used for evaluating and predicting soil erosion in Ethiopian watersheds, but most of them used the Soil and Water Assessment Tool (SWAT) (see, among many others, Gessese & Yonas, 2008; Senti et al., 2014; Yesuf et al., 2015; Ebabu et al.2019; Megersa et al., 2019; Mariye et al., 2022; Gebretekle et al., 2022). These studies confirmed that poor land use practices, improper land management and absence of appropriate soil conservation measures have been major causes of soil erosion and land degradation problems, with consequent sedimentation in Ethiopian reservoirs (Tefera et al.2010; Ayana et al.2012; Dibaba et al.2021).

During the past decades, the Fincha watershed, part of the Blue Nile River basin, has experienced dynamic LULC changes in the degradation of natural woodlands (Dibaba et al., 2021; Regasa et al., 2021). According to Leta et al. (2021) and Kenea et al. (2021), such LULC variations can have both long- and short-term temporal and spatial effects on the watershed hydrology, and consequently on the soil erosion and sediment yield entering the dam reservoirs located in the watershed (Dibaba et al., 2021b).

The present investigation aims to evaluate the impact of LULC change on sediment yield entering the Fincha reservoir, looking at past trends (1989, 2004, 2019 years) and predicting future scenarios (2030, 2040, 2050 years). LULC scenarios were developed based on historical data and future predictions (Regasa & Nones, 2022) while hydrological changes and consequent sediment yield were computed by applying the SWAT model, given its reliability in modelling water and sediment loading (Gassman et al., 2007). The present findings contribute to a better understanding of soil erosion processes and consequences in a poorly gauged basin, giving useful insights on future management strategies and mitigation measures that can be applied for reducing sediments entering the Fincha reservoir, eventually contributing to assuring a longer service life.

2. Materials and Methods

2.1 SWAT model description

The Soil and Water Assessment Tool (SWAT) was developed by the United States Department of Agriculture (USDA), and is a continuous-time, semi-distributed, process-based watershed model. SWAT was initially developed to predict the impact of land management practices on water, sediment and chemical yields in agricultural watersheds (Arnold et al., 1998; Winchell et al., 2007) but, since then, it has been widely used to understand the hydrological cycle in general, simulating the effect of land use hydrology, water quality and ecosystem services, to eventually derive sediment yield and soil management practices (e.g., Qiu et al., 2014; Xue et al. 2014; Dibaba et al. 2021; Kenea et al., 2021; Lin et al., 2022). There is ample literature proving the validity of SWAT in modelling soil erosion and transport processes (e.g., Setegn et al., 2010; Phuong et al. 2014; Cousino et al. 2015; Djebou et al. 2018; Dakhlalla & Parajuli, 2019; Khanchoul et al. 2020). SWAT divides a watershed into sub-watersheds, connected through a stream channel. Further, each sub-watershed is divided into Hydrologic Response Units (HRUs), which represent a unique combination of soil, land use and slope type in a sub-watershed (Arnold et al., 2012; Rathjens & Oppelt, 2012). In SWAT, hydrology and sediment are simulated at the HRU level, and then the outputs are summarized first at the sub-watershed level, and then at the watershed level, routing these quantities through the stream network (Neitsch et al., 2011). SWAT can account for that, simulating all the effects of soil erosion and climate change on water supply properly (Krysanova & White, 2015).

2.2 Study Area

The Fincha watershed is in Ethiopia's Horroo Guduruu Wallaggaa Oromiyaa regional state, in the Upper Blue Nile Basin, about 300 km from Addis Ababa. It is geographically located between latitudes 9°9′53″ N to 10°1′00″ N and longitudes 37°00′25″ E to 37°33′17″ E, as shown in the map (Figure 1).

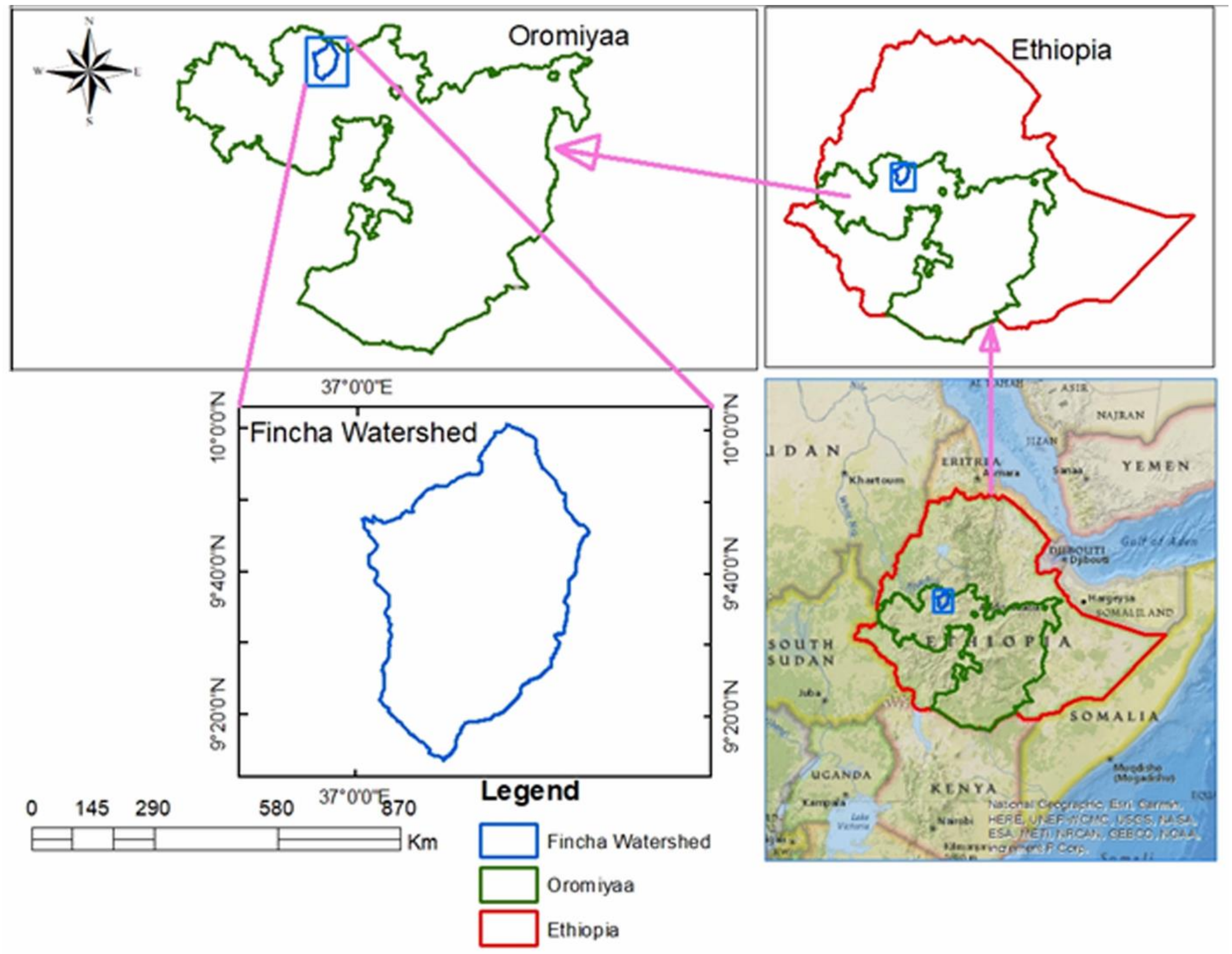

Figure 1. Location of the Fincha watershed, Oromiyaa regional state, Ethiopia.

The region is defined by four distinct seasons: Summer, June to August, with heavy rains; Harvest season occurs from September to November, winter, which lasts from December to February, is illustrated by morning frost, particularly in January. Spring, from March to May, is the hottest season, with showers on occasion. The annual rainfall in the study area ranges from 1367 to 1842 mm, with the Northern lowlands receiving the least rain and the Southern and Western highlands receiving more than 1500 mm (Regasa and Nones, 2022). The main rainy season is from June to September, where the average precipitation is around 1604 mm with peaks between July to August.

According to studies conducted by Regasa and Nones (2022) and Leta et al. (2021), natural resources such as the Fincha, Amarti, and Nashe lakes not only contribute to the national economy by generating hydroelectric power, but are also used to irrigate large sugar cane fields. Because of its downstream connection to the Nile basin and intensive agriculture, the area is of national and international interest in hydro politics.

2.3 Available dataset

The SWAT model requires multiple pieces of information, which come from different sources (Table 1). In detail, the model inputs are Digital Elevation Model (DEM), LULC maps, soil data, weather data (relative humidity, precipitation, solar radiation, temperature, and wind speed), water flow and sediment data.

Table 1. Available data and sources.

Type	*Data*	*Resolution/year*	*Source*
Spatial Data	Digital elevation Model (DEM)	30m / 2019	Ministry of Water, Irrigation, Energy (MOWIE), Ethiopia
	Land use land cover	30m / 1989, 2004, 2019, 2030, 2040, 2050	1989, 2004, 2019 derived from Landsat images 2030, 2040, 2050 predicted by Land Change Modeler (Regasa & Nones, 2022)
	Soil		Ministry of Water, Irrigation and Energy (MOWIE), Ethiopia

Meteorological Data	Precipitation, Temperature, Relative humidity, Solar radiation, Wind speed	1986-2019 daily	Metrological National Agency, Ethiopia
Hydrological Data	Stream flow	1986-2008 daily	Ministry of Water, Irrigation, and Energy (MOWIE), Ethiopia
Sediment Data	Recorded sediment	1986-2008	Ministry of Water, Irrigation, and Energy (MOWIE), Ethiopia

2.3.1 Meteorological data

The analysis was performed using daily observed weather data covering the period 1986-2019 years. These data include precipitations, maximum and minimum temperatures, solar radiation, wind speed and relative humidity, refer to ten gauging stations collected from the Ethiopian metrological agencies of are Alibo, Fincha, Gebete, Hareto, Homi, Jermet, Kombolcha, Nashe, Shambu and Wayyu. The statistical software *Xlstat* was used to fill gaps in the meteorological dataset.

2.3.2 Soil data

Soil information was obtained from the Ethiopian Ministry of Water, Irrigation and Energy (MOWIE), and they were pre-processed to follow the Food and Agricultural Organization (FAO) guidelines as stated in Pennock (2019). Ten soil types can be recognized in the Fincha watershed: Dystric Vertisols, Eutric Cambislos, Eutric Leptosols, Eutric Vertisols, Haplic Alisols, Haplic Arenosols, Haplic Phaeozems, Rhodic Nitisols, Chromic Luvisols, Water and Marsh (Figure 2b).

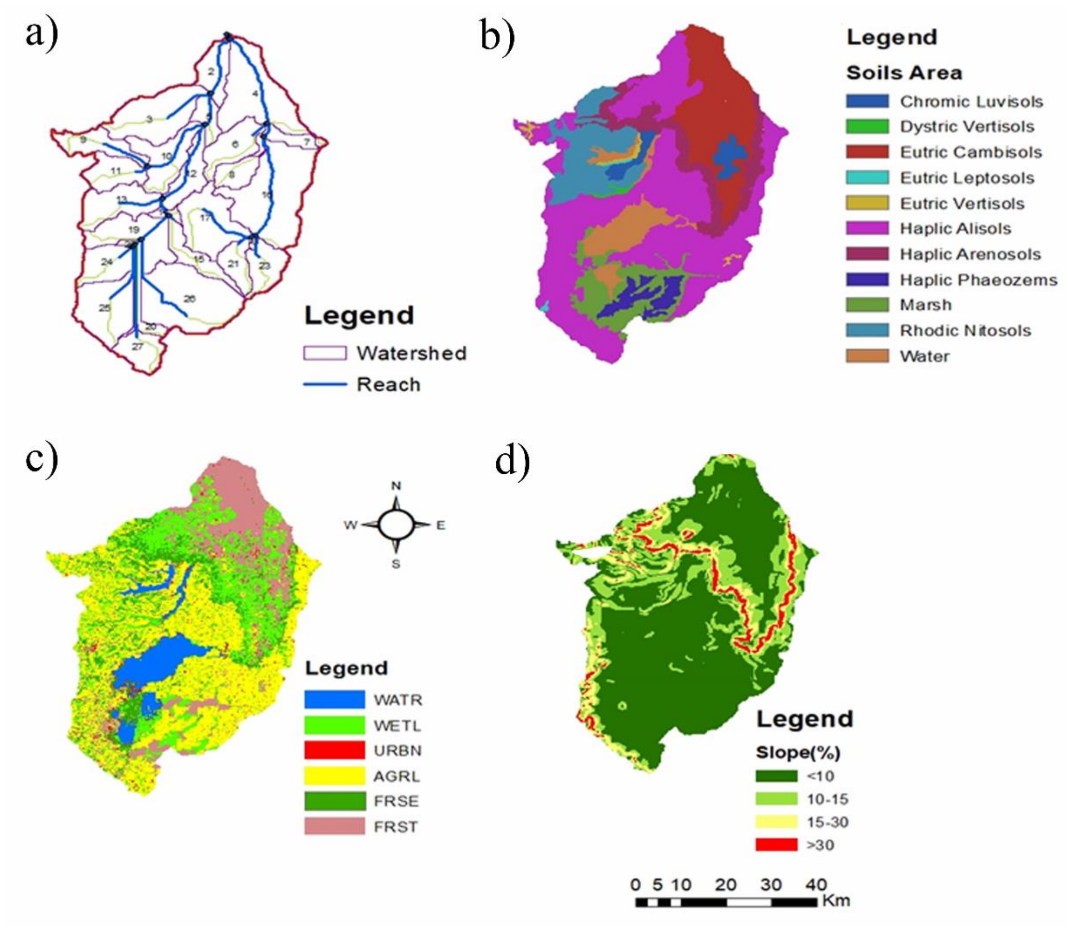

Figure 2. Main characteristics of the study area: a) river system and sub-watersheds; b) soil types; c) LULC of 2019; d) terrain slope.

2.3.3 Land use land cover

Land use is a key SWAT model input that influences surface runoff, evapotranspiration, erosion, nutrients and pesticide load in a watershed. The land use land cover (LULC) data used in the present research were previously described by Regasa and Nones (2022), who investigated LULC in past (1989, 2004, 2019) and future (2030, 2040, 2050) years. The area was classified into six classes: waterbody, grass/swamp, built-up, agricultural land, forest, shrub (Figure 2c). The LULC data set was reclassified into six major land classes as it is for use in SWAT. This reclassification was conducted because the SWAT model needs standard names such as WATR, WETL, URBN, AGRL, FRSE and FRST for waterbody, grass/swamp, built-up, agricultural land, forest, and shrub respectively.

2.3.4 Slope

Multiple slope classes were defined and then used to delineate SWAT HRU having the same slope, based on a 30m x 30m DEM of the Fincha watershed and using the Arc-GIS spatial analysis tool. When defining the hydrologic response unit, Arc-SWAT allows the integration of up to five slope classes. In addition, the SWAT model allows you to select a single or multiple slope class. As a result, the slope classes used in this study were broken down into four classes (10%, 15%, 25%, >30%) to represent the variation in the topography of the Fincha watershed (Figure 2d).

2.3.5 Sediment rating curve

One of the most crucial pieces of information for estimating soil erosion in a hydrological study knows sediment characteristics. To overcome the lack of continuous measurements, a sediment rating curve was developed to relate daily stream flow to sediment data recorded at the outlet of the Fincha watershed. Such a curve can show how stream flow affects the rate of sediment movement (Assfaw, 2020), but its reliability high depends on the available dataset

To simulate sediment yield and stream flow, SWAT needs, as model input, sediment, and stream flow data with a continuous time step. Due to the lack of continuous sediment data, these were derived by applying an empirical sediment rating curve to the simulated daily stream flow. Such an approach is generally used when there are few long-term and trustworthy records of sediment concentrations (Jilo et al., 2019).

Following literature evidence (e.g., Asselman, 2000; Horowitz, 2003; Franzoia & Nones, 2017, Assfaw, 2019), a general relationship between sediment concentrations and river discharge can be written as

$$Q_s = aQ_f^{\ b} \tag{1}$$

where Q_s is the sediment load in ton day^{-1}, Q_f represents the stream flow in m^3 s^{-1}, while a and b are regression constants to be determined from a regression between measured sediment and water flows.

In the study case, the obtained sediment data was in mg l^{-1}, but this concentration was converted to ton day^{-1} via the equation

$$Q_s = 0.0864 * C * Q_f \tag{2}$$

where C indicates the suspended sediment concentration (mg l^{-1})

Using the data obtained from MOWIE and reporting flow and sediment data measured at the Fincha gauging station between 1986 and 2008, a sediment rating was created (Figure 3). The regression constants a and b were found to be 2.9508 and 1.2056, respectively.

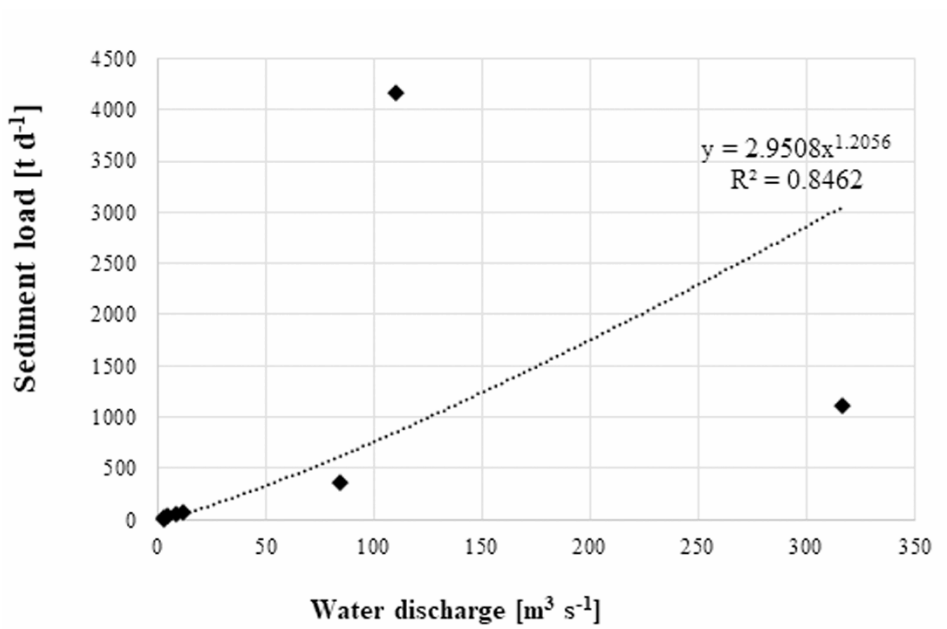

Figure 3. Sediment rating curve for the period 1986-2008. Data were measured at the Fincha gauging station (source: MOWIE).

2.4 SWAT model setup

From the SWAT website (swat.tamu.edu), Arc-SWAT version 2012.10 4.19 was downloaded, and its interface was linked to Arc-GIS 10.3.1 for the modelling. This latter process involves setting up a SWAT project, defining the spatial extent of the analysis (watershed, sub-watersheds, HRUs), writing and editing SWAT input, and performing the simulations. Following the collection of data, all input data were prepared, the watershed and the HRUs were defined, and the classification of land use, soil, and slope was included in the model.

Based on the water balance equation (Swami and Kulkarni, 2016), SWAT simulates the hydrological cycle:

$$SW_t = SW_o + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \qquad (1)$$

where SW_t is the last soil water content (mm), SW_o is the first soil water content on day *i* (mm), *t* indicates the time (days), R_{day} is the amount of precipitation on day *i* (mm), Q_{surf} represents the amount of surface runoff on day *i* (mm), W_{seep} is the amount of water entering vadose zone from the soil profile on day *i* (mm), E_a is the amount of evapotranspiration on day *i* (mm) and Q_{gw} indicates the amount of return flow on day *i* (mm).

In our study, the SWAT model was applied to estimate, at the daily scale, hydrological components such as surface run-off, evapotranspiration, and sediment yield. Sediment yield was estimated at the HRU level, through a Modified Universal Soil Loss Equation (MUSLE) (Khelifa et al., 2016; Sahar et al., 2021)

$$Sed = 11.8(Q_{surf} * q_{peak} * Area_{HRU})^2 * K * C * P * LS * CFRG \qquad (2)$$

where *Sed* is sediment yield in metric tons per day, Q_{surf} is the surface runoff volume (mm), q_{peak} is the peak run-off rate (m^3/s), $Area_{HRU}$ is the area of HRU (ha), *K* is the soil erodibility factor, *C* is the cover and management factor, *P* is the practice support factor, LS is the topographic factor and *CFRG* is the course fragment factor.

2.4.1 Watershed delineation

The watershed and the sub-watersheds were delineated by using the 30m-resolution DEM of the Fincha basin, via defining the stream network in SWAT and considering flow accumulation and water flow direction. SWAT models enable users to delineate watersheds and sub-watersheds using Digital Elevation Models (DEMs) by expanding the Arc-GIS and spatial analyst extension function. Watershed and sub-watershed delineation was accomplished through a series of steps, including DEM setup, stream definition, inlet outlet definition, watershed outlet selection and definition, and finally sub-basin parameter calculation (Figure 2a).

The Arc SWAT model interface by default proposes the minimum and maximum watershed area, as well as the size of the sub-watershed in hectares to define the minimum drainage area required to form the stream's origin. The smaller the threshold area, the more detail of the drainage network, the greater the number of sub-watersheds, and the higher the number of HRUs. However, more processing time and computer space are required. As a result, the model's proposed threshold was used to determine the optimal size of the threshold area as described in section 2.4.2 below.

2.4.2 Hydrologic Response Units

HRUs were defined based on the topographical characteristics of the terrain as derived from the DEM and assigned to each sub-watershed based on a threshold value for LULC, soil, and slope categories. According to Megersa et al., (2021), a threshold of 10% was imposed in defining HRUs, to exclude areas characterized by small land uses and slope classes. Consequently, the Fincha watershed was divided into 27 sub-watersheds and then subdivided into 234 HRUs. It is worth reminding that only 9 of these sub-watersheds are located upstream of the Fincha Dam, and are therefore contributing to the sediment yield entering the dam.

2.4.3 Model calibration and validation

A sensitivity analysis is needed to investigate the model's capacity to adequately predict water stream flow and sediment yield (Anaba et al., 2016), and this was done via the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) interface (Mekuriaw, 2019) combined with the SUFI-2 approach (Leta et al., 2021). SWAT Calibration and Uncertainty Procedures (SWAT-CUP), a program for integrated sensitivity analysis, calibration, and validations, were used to analyze the uncertainties of SWAT model prediction (Dibaba et al., 2021). In this investigation, the sensitivity analysis was performed using the SUFI-2 techniques and looking at the water discharge - sediment load data measured at the outlet of the Fincha Reservoir (at Fincha Dam) during the period 1986-2008.

To perform model calibration and validation, the stream flow and sediment data were divided into two periods, and an initial warm-up period was also taken into consideration. The initial three (1986-1988) years were chosen as the warm-up period, while the calibration was performed for the 1989-2002 years while 2003-2008 were utilized to validate the SWAT model.

To test the goodness of fit between monthly simulated and observed values, the model's performance was assessed using the coefficient of determination (R^2), the Nash-Sutcliffe simulation efficiency (*NSE*), and the per cent bias (*PBIAS*).

Determination coefficients can range from 0 (inadequate model) to 1 (the model perfectly fits the data), and, typically, values R^2 larger than 0.6 indicate good correlation (Leta et al. 2021).

The *NSE* values can reach a maximum of 1 (perfect fit), while a negative *NSE* value indicates that the model's performance is inferior to that obtained using the observations' mean as a predictor (Jilo et al., 2019). The simulation efficiency is classified as unsatisfactory, satisfactory, good, or very good if $NSE<0.50$, $0.5<NSE<0.65$, $0.65<NSE<0.75$, $0.75<NSE<1$, respectively (Leta et al., 2021).

PBIAS assesses the typical tendency of the simulated data to differ from the observed data in size or frequency, and lower *PBIAS* values indicate better simulation results. Moriasi et al. (2007) define *PBIAS* positive values as a model underestimation, while negative values as a model overestimation.

According to Yasir et al. (2020) and Dibaba et al. (2021), the following equations were applied to determine R^2 (eq. 3), *NSE* (eq. 4) and *PBIAS* (eq. 5):

$$R^2 = \left[\frac{\sum_{i=1}^{n}(Q_{Obs}-\bar{Q}_{Obs})(Q_{cal}-\bar{Q}_{Cal}}{\sum_{i=1}^{n}(Q_{Obs}-\bar{Q}_{Obs})^2\sum_{i=1}^{n}(Q_{Cal}-\bar{Q}_{Cal})^2}\right]^2 \tag{3}$$

$$A = 1 - \frac{\sum_{i=1}^{n}(Q_{Obs}-Q_{Cal})^2}{\sum_{i=1}^{n}(Q_{Obs}-\bar{Q}_{Obs})^2} \tag{4}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(Q_{Obs}-Q_{Calc})*100}{\sum_{i=1}^{n}Q_{Obs}} \tag{5}$$

where Q_{Obs} is the actual variable, $\bar{Q}_{\mathrm{Obs}}$ is the time average of the variable Q_{Obs}, Q_{Cal} is the simulated variable and $\bar{Q}_{\mathrm{Cal}}$ is its time average. It is worth noticing that these equations are valid for both water flow and sediment data.

2.5 Scenarios simulation

Using scenario-based simulations, the effects of current and future LULC changes on watershed sediment yield were assessed for the period 1989-2050. This was done by creating six scenarios (historical reference years 1989, 2004, 2019; future predicted 2030, 2040, 2050) accounting for different LULC conditions (Regasa & Nones, 2022). A fixing-changing method was applied to investigate the effects of LULC change (Leta e al., 2021): SWAT was run with changing LULC maps, but all the other modelling parameters were kept constant as derived from the model validation (Gessesse et al., 2015). The sediment yield was computed separately for the entire Fincha watershed (27 sub-watersheds) and the region upstream of the Fincha Dam (9 sub-watersheds).

Pearson's correlation method (Aga et al., 2020) was used to assess the variations in LULC classes and the sediment yields, while the pair-wise Pearson correlation matrix was applied to detect linear correlations.

3. Results

3.1 Sensitivity analysis

A sensitivity analysis for the simulated stream flow and sediment was carried out to determine the most sensitive parameter with the greatest impact on model results. According to the SWAT manual and the literature (Khelifa et al., 2017, Yuan & Forshay, 2019, Daramola et al., 2019), nine (Table 2) and seven (Table 3) parameters for stream flow and sediment were respectively selected as the initial input for the model sensitivity analysis.

The sensitivity analysis was based on the SUFI-2 algorithm techniques (Arnold et al., 2013). The *p*-value and the *t*-stat value were used to assess the sensitivity of each parameter and then rank it, with rank 1 indicating the most sensitive parameter. Statistically, bigger absolute *t*-stats and lower *p*-values mean that a parameter is significant. On the other part, a high *p*-value indicates that there is no correlation between changes in the predictor values and the response variable (Pandey et al., 2021).

Table 2. Stream flow parameters with range and fitted value, as derived from the sensitivity analysis performed using SUFI-2. Their rank was established based on P-value.

Parameter Name	Description	Range	Fitted value	Calibration		
				t-stat	*p*-value	Rank
V_GW_DELAY.gw	Groundwater delay (days)	0 - 500	21.25	-9.891	0.000	1
R_CN2.mgt	SCS runoff curve number II	-25 - 25	-15.625	2.391	0.018	2
V_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H2O)	0 - 5000	2012.5	-2.022	0.045	3
R_CH_N2.rte	Manning's "n" value for the main channel	0 - 1	0.7575	0.717	0.474	4
R_SOL_AWC(1).sol	Available water capacity of the 1st	-25 - 25	6.875	0.699	0.486	5

	soil layer (mm H2O mm soil−1)					
R_SOL_K(1).sol	Saturated hydraulic conductivity at the 1st soil layer (mm h−1)	-25 - 25	9.875	0.255	0.799	6
R_SLSUBBSN.hru	Average slope length (m)	0 - 150	133.875	0.153	0.878	7
R_RCHRG_DP.gw	Deep aquifer percolation fraction	0 - 1	0.6475	-0.099	0.921	8
V_ALPHA_BF.gw	Base flow alpha factor (1 day−1)	0 – 1	0.3125	0.060	0.952	9

Table 3. Sediment parameters with range and fitted value, as derived from the sensitivity analysis performed using SUFI-2. Their rank was established based on P-value.

Parameter Name	Description	Range	Fitted value	Calibration		
				t-stat	P value	Rank
R_SPEXP.bsn	Exponential factor for channel sediment routing	0 - 2	1.71	-9.85	0.00	1
R_LAT_SED.hru		1 - 1000	242.50	-5.07	0.00	2

R_CH_COV2.rte		0 - 1	0.56	-3.06	0.00	3
R_SPCON.bsn	linear factor for channel sediment routing	0 – 0.01	0.005	-1.95	0.05	4
R__CH_COV1.rte		0.01 – 0.06	0.11	-1.53	0.13	5
R__PSP.bsn	Peak rate adjustment factor for sediment routing in the sub-basin (tributary channels)	0 - 1	0.88	-0.42	0.67	6
R__USLE_P.mgt	USLE support Practice factor	0 - 1	0.208	-0.31	0.75	7

3.2 Calibration and validation

Using the observed monthly stream flow and sediment at Fincha reservoir close to the Fincha Dam outlet from 1986 to 2008 years, the model parameters of SWAT were calibrated and validated. The warm-up period 1986-1988 was used to reduce the impact of the model's initial conditions during the model's initial stage of operation, while the calibration period lasted from 1989 to 2002, and the validation period from 2003 to 2008.

The model is very effective at simulating the stream flow (Figure 4), as shown by the values computed for the calibration and validation phases, summarized in Table.

Table 4. Simulation of water discharge: model performance during the calibration and validation phases.

Statistical test	*R^2*	*NSE*	*PBIAS*
Calibration	0.83	0.83	8.3
Validation	0.84	0.76	12.2

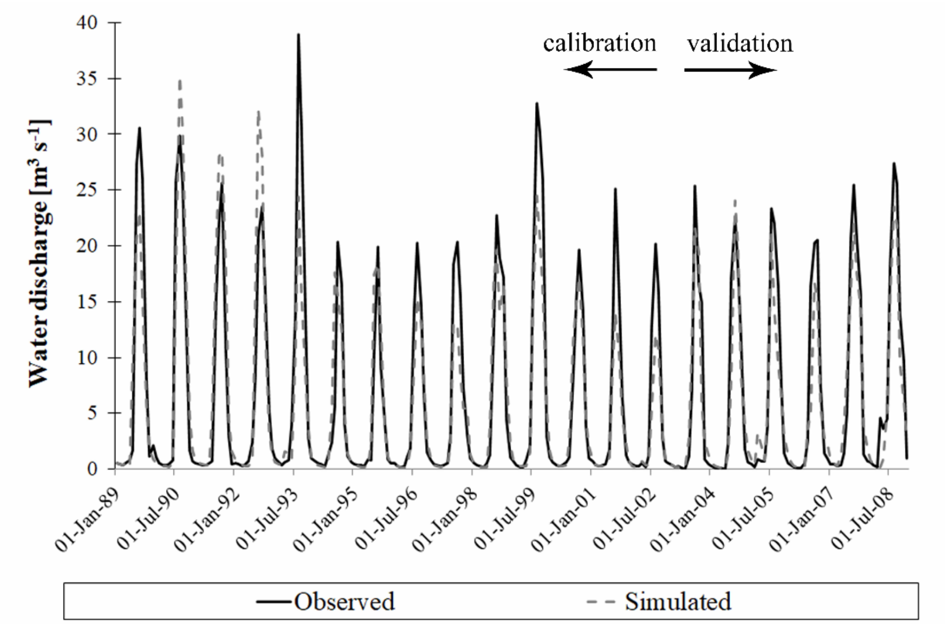

Figure 4. Comparison between computed and measured water discharge at the Fincha Dam outlet, during the calibration (1989-2002) and validation (2003-2008) phases.

The SWAT model was also calibrated and validated in terms of monthly sediment transport (Table 5). A positive *PBIAS* for both periods indicates that the overall expected sediment production had been underestimated, mainly due to problems in detecting sediment peaks (Figure 5).

Table 5. Simulation of sediment yield: model performance during the calibration and validation phases.

Statistical test	R^2	*NSE*	*PBIAS*
Calibration	0.83	0.63	8.3
Validation	0.86	0.72	12.2

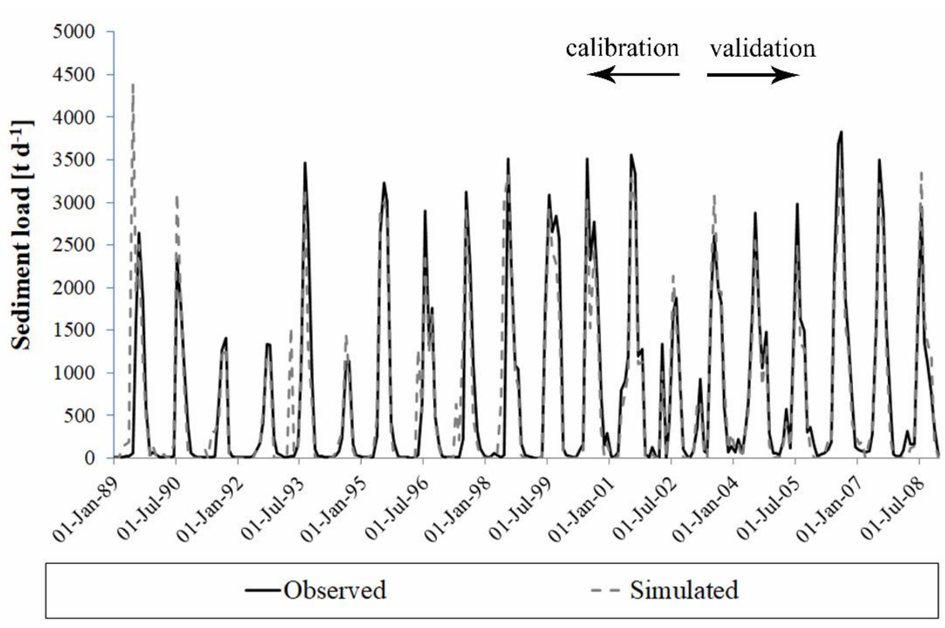

Figure 5. Comparison between computed and measured sediment load at the Fincha Dam outlet, during the calibration (1989-2002) and validation (2003-2008) phases.

3.3 Sediment yield estimation

The SWAT model was applied to simulate sediment yield in 27 sub-watersheds (see Section 2.4.2). Based on the approach proposed by Dibaba et al (2021), these sub-watersheds were classified in terms of soil loss (Table 6).

Table 6. Classification in terms of annual soil loss and severity.

Annual soil loss [t ha^{-1}]	Severity
<11	Low
11-18	Moderate
18-25	High
25-50	Very high
50-75	Severe
>75	Very severe

This classification pointed out significant dissimilarities across the Fincha watershed (Figure 6), which are mainly connected with the different LULC of each sub-watershed, as discussed in the next sections.

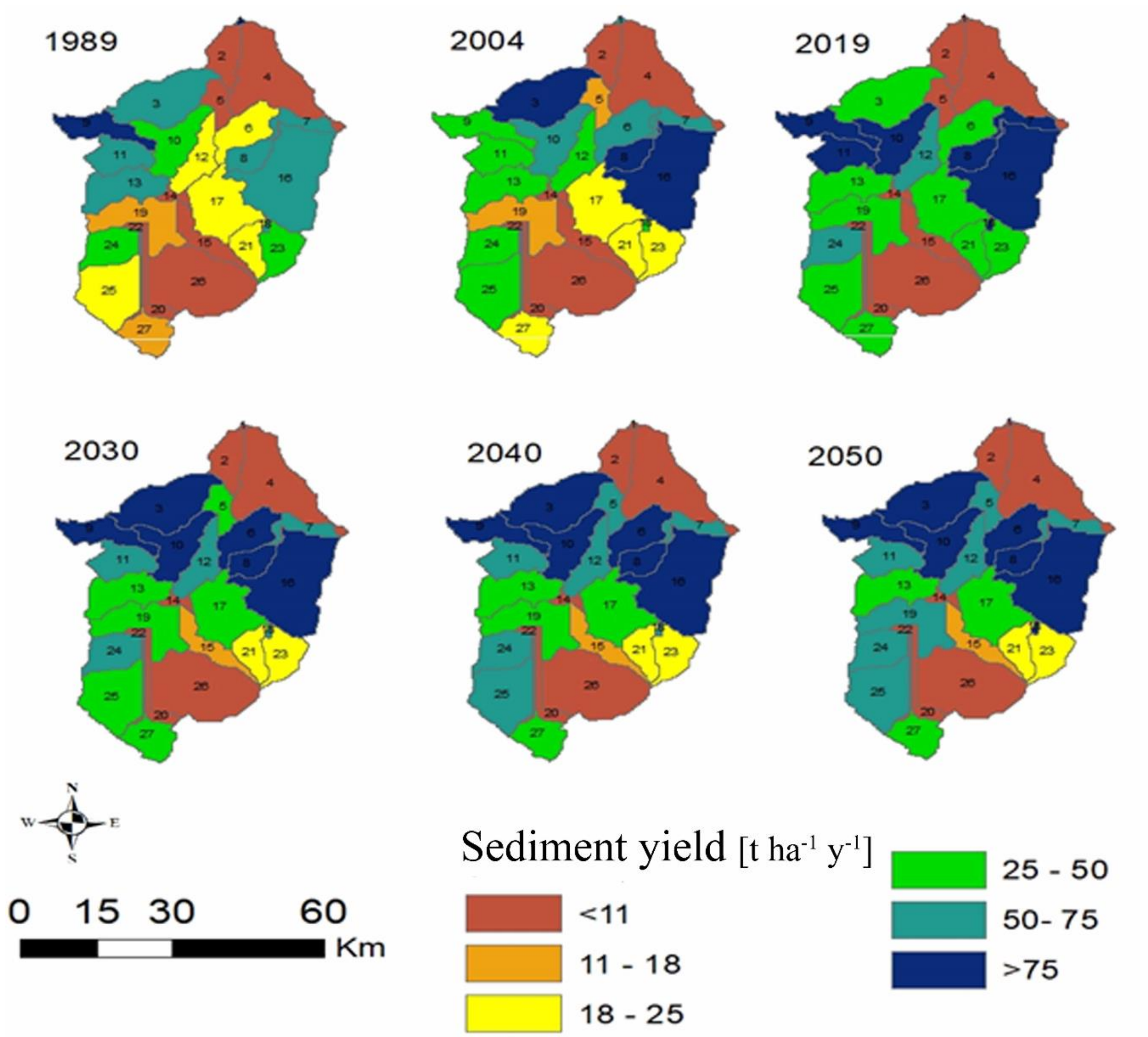

Figure 6. Spatial distribution of the sediment yield, subdivided for each sub-watershed.

The annual sediment yield in the Fincha watershed ranges from 0.36 to 83.74, from 0.80 to 113.72, from 0.28 to 121.96, from 0.48 to 117.92, 1.06 to 162.96, from 1.12 to 183.80 t ha^{-1} for 1989, 2004, 2019, 2030, 2040, 2050 scenarios, respectively. The annual average sediment yield was computed as 32.51, 34.05, 41.20, 46.20, 51.19, 53.98 t ha^{-1} for the same six scenarios, respectively, meaning an increase of 8.69 t ha^{-1} from 1989 to 2009, while the increase forecasted for the next 30 years (2019 to 2050) will be even more significant, reaching 12.78 t ha^{-1}.

Focusing only on the nine sub-watersheds upstream of the Fincha Dam, and therefore contributing to feeding the reservoir with sediments, the average annual sediment yield spans from 0.36 to 40.06, from 0.40 to 48.96, from 0.28 to 61.72, from 0.94 to 64.42, from 1.06 to 68.78 and from 1.12 to 69.96 t ha^{-1} for 1989, 2004, 2019, 2030, 2040, 2050, respectively. The annual average sediment yield for these scenarios is 6.71, 8.49, 12.30, 13.69, 14.57 and 15.19 t ha^{-1}, respectively. In Table 7 the results are summarized in terms of severity, showing an increase in areas affected by high to very severe erosion.

Table 7. Annual soil erosion and its severity for past and future scenarios of Fincha reservoir

Year	Annual soil loss [t ha^{-1}]	Severity	Area [ha]	Area in per cent [%]
1989	<11	Low	14348.00	17.77
	11 – 18	Moderate	23132	28.64
	18 – 25	High	34044	42.16
	25 – 50	Very high	9232	11.43
	50 – 75	Severe	0	0.00
	>75	Very severe	0	0.00
2004	<11	Low	14348	17.77
	11 - 18	Moderate	14740	18.25
	18 - 25	High	25472	31.54
	25 - 50	Very high	26196	32.44
	50 - 75	Severe	0	0.00
	>75	Very severe	0	0.00

2019	<11	Low	14348	17.77
	11 - 18	Moderate	0	0.00
	18 - 25	High	0	0.00
	25 - 50	Very high	57176	70.80
	50 - 75	Severe	9232	11.43
	>75	Very severe	0	0.00
2030	<11	Low	6996	8.66
	11 - 18	Moderate	7352	9.10
	18 - 25	High	0	0.00
	25 - 50	Very high	57176	70.80
	50 - 75	Severe	9232	11.43
	>75	Very severe	0	0.00
2040	<11	Low	6996	8.66
	11 - 18	Moderate	7352	9.10
	18 - 25	High	0	0.00
	25 - 50	Very high	40212	49.79
	50 - 75	Severe	26196	32.44
	>75	Very severe	0	0.00
2050	<11	Low	6996	8.66
	11 - 18	Moderate	7352	9.10
	18 - 25	High	0	0.00
	25 - 50	Very high	25472	31.54
	50 - 75	Severe	40936	50.69

	>75	Very severe	0	0.00

Even if the average annual sediment yield of sub-watersheds locates upstream of the Fincha Dam is lower than the average annual sediment yield of the whole watershed, the sediment amount entering annually the reservoir is still very high. In detail, 1.44, 1.85, 2.75, 3.08, 3.27, 3.42 mil t in 1989, 2004, 2019, 2030, 2040, 2050, respectively, can enter the dam lake (Figure 7).

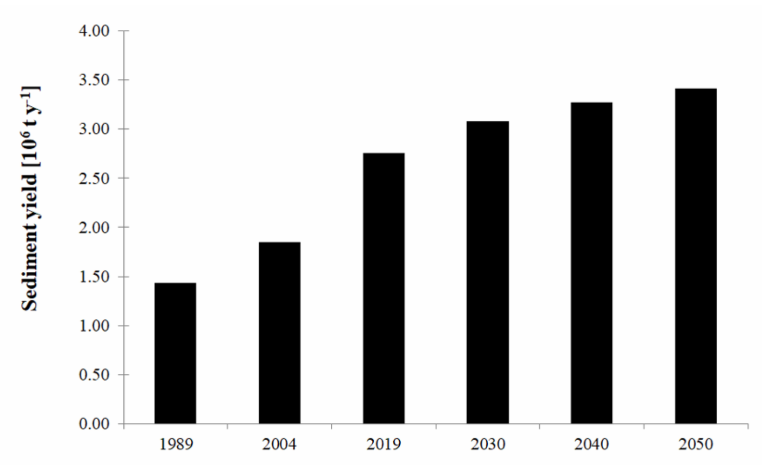

Figure 7. Annual sediment yield entering the Fincha Dam reservoir from the sub-watersheds located upstream.

4. Discussion

The observed and simulated water and sediment discharges at the Fincha Dam showed an overall good agreement, indicating the reliability of the SWAT model in simulating these parameters in data-scarce regions. However, the model was unable to adequately reproduce the peaks in both water discharge and sediment yield. The underestimation of peak water flows generally results in an underestimation of the sediment peaks (Akoko et al., 2021), and such an underestimation is also a significant source of error in defining the overall sediment load of the watershed.

Moreover, the reliability of SWAT in estimating sediment yield is highly dependent on the availability of long-term datasets. In Ethiopia, long-term monitoring data are very rare, especially in terms of sediment information. To overcome this issue, in the present work a sediment rating curve characterized by a strong correlation (R^2=0.86) between recorded sediment and water flow data was implied.

Based on this sediment rating curve, the annual soil loss was evaluated, as well as the areas characterized by a major soil loss (hotspots), eventually prioritizing management strategies in these zones. For the entire Fincha watershed, the mean annual soil loss rate was calculated as 32.51 t ha^{-1}, 34.05 t ha^{-1}, 41.20 t ha^{-1}, 46.20 t ha^{-1}, 51.19 t ha^{-1}, 53.98 t ha^{-1} in 1989, 2004, 2019, 2030, 2040, 2050, respectively. This translates into an increase of annual soil loss of 8.69 t ha^{-1} during the last 30 years (1989-2019), and a forecasted increase of 12.78 t ha^{-1} for the next three decades, which will further negatively impact the overall basin as well as the reservoirs located therein.

As pointed out by Dibaba et al. (2021), tolerable soil loss is needed for maintaining ecosystem services without compromising the soil's ability to continue providing those services in the future. The maximum tolerable soil loss (0-11 t ha^{-1} $year^{-1}$) estimated for Ethiopian watersheds is much lower than the estimated mean annual soil loss rate in the current study area (Girmay et al., 2020; Ayalew et al., 2022), pointing out that the Fincha watershed is at very high of soil erosion. On the other part, the Fincha soil erosion rates are much lower than other local scale studies, which estimated an annual soil loss rate of 377.26 t ha^{-1} in the Chogo watershed, located very close to the current study area (Negash et al., 2021).

The mean annual sediment yields of the nine sub-watersheds located upstream of the Fincha Dam span will increase from 13.42 t ha^{-1} in 1989 to 30.38 t ha^{-1} in 2050. As the estimated mean annual soil loss rate is considerably higher than the maximum tolerable soil loss limit of 11 t ha^{-1}, also this area is threatened by high erosion, with consequent negative effects on the socio-economy. More than 85% of the Ethiopian population depends on agriculture for living, therefore physical soil and nutrient losses can lead to food insecurity.

According to the estimated rates of mean annual soil loss, the erosion risk was classified into six classes (Table 6). The proportion of area at low erosion risk covered around 18% of the basin during the past (reference years 1989, 2004, 2019) while a decrease is forecasted for the future (around 9% in 2030, 2040, 2050). On the other part, areas exposed to high erosion risk will increase, mainly because of deforestation in favour of agricultural land, expansion of urban areas and grassland, growth and relocation of the population. This dynamic and rate of soil loss is a characteristic of many highland areas in Ethiopia (Weldu Woldemariam & Edo Harka, 2020), pointing out that the problem of soil erosion should be tackled at the national level, rather than with very local policies.

The soil erosion risk had shown a high spatial variation across the study landscape (Figure 6): low-risk areas were predicted downstream of the Fincha Dam, while areas characterized by the highest erosion risk are in the northwestern and eastern parts of the Fincha watershed.

Relatively less eroded areas were situated at lower elevations in the eastern and western parts of the sub-basin, where the slope inclination is below 10% with the above-mentioned factors made the area generate high soil loss risks. Similar results have been reported by earlier studies that directly correlated soil loss rate to terrain slope (Dibaba et al., 2021). According to Regasa et al. (2021), the communities displaced from the reservoir areas were forced to resettle downstream of the dam, in areas characterized by lower soil loss. However, these communities were forced to relocate without receiving fair compensation because of the expansion of the number and dimension of reservoirs for hydropower production, taking them away from their farmland (Dibaba et al., 2020). Residents found it difficult to stay and were compelled to relocate due to the increased resettlement on unproductive lands and the relative depreciation of agricultural land, which results in further increasing soil erosion.

This study pointed out that all the sub-watersheds of the Fincha watershed are highly threatened by soil erosion, and therefore require management and mitigation strategies to safeguard the environment and reduce the sediment yield entering the Fincha reservoir. However, such strategies could be costly and time-consuming, and cannot be applied at the same time all over the watershed. In this respect, the present investigation can provide information on what areas should be prioritized, but more studies are needed to propose effective management strategies to reduce soil erosion that also account for the sustainable socioeconomic development of the area.

5. Conclusions

Using the Fincha watershed as a case study, the present research focused on understanding, via a modelling approach, the impact of LULC changes on soil erosion, comparing past trends with future predictions. It was found that the present LULC changes, which are favoring agricultural land and settlements over natural forests, have a detrimental impact on soil erosion, which increased from 32.51 t ha^{-1} $year^{-1}$ in 1989 to 41.20 t ha^{-1} $year^{-1}$ in 2019, and will increase till 53.98 t ha^{-1} $year^{-1}$ in 2050 at the watershed scale. Such soil loss translates into sediment yield transported in the Fincha Dam reservoir, which was estimated to increase from 1.44 mil t in 1989 to 3.42 mil t in 2050, eventually reducing the lifetime of the dam.

Based on the estimated rate of mean annual soil loss, the erosion risk was classified into six classes, pointing out that over 91% of the watershed is forecasted at high to severe erosion risk, with severe erosion located in the central, northeastern, and northwestern sub-watersheds. As soil erosion represents a major threat to the current socio-economic development of the area, the classification proposed here could serve as a basis to prioritize future management strategies, aiming to reduce the impact of soil loss on the local environment and population.

Author Contributions

Conceptualization, M.S.R. and M.N.; writing-original draft preparation, M.S.R. and M.N.; literature review, M.S.R. and M.N.; modelling, M.S.R.; data analysis, M.S.R.; supervision, M.N.; project administration, M.N.; funding acquisition, M.N.

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Data availability

The data used in the present research are available at the IG PAS Data Portal (dataportal.igf.edu.pl) and from the corresponding author.

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