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Testing of the revised universal soil loss equation for soil erosion assessment in the Ouringa River Basin

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ABSTRACT

The urban Oringa River basin is facing rapid degradation due to population growth and land use changes. The integration of remote sensing, GIS, and the revised universal soil loss equation provides an effective approach to monitor and to evaluate soil erosion in this region. The study aims to assess soil loss in the Ouringa River basin in Morocco using the RUSLE model, integrated with remote sensing and GIS. The RUSLE model includes several key factors that contribute to erosion, including rainfall erodibility (R), soil erodibility (K), slope length and steepness (LS), conservation practices (P), and vegetation cover (C). The results indicate that the Oringa River basin has been facing continuous soil erosion for four decades, with annual losses exceeding 200 tons per hectare initially and continuing through 1981–2022. The analysis reveals that 60–66% of the area experienced minor soil erosion, remaining below 100 tonnes per hectare. However, 20–23% of the land showed low erosion (100–200 tonnes per hectare), while 8–10% experienced moderate erosion (200–400 tonnes per hectare). A smaller proportion, 4–5%, experienced moderate erosion (400–1000 tonnes per hectare), and 2% experienced severe erosion exceeding 1000 tonnes per hectare. Effective soil management is critical to mitigate these losses and protect watersheds. Analysis of land use types revealed by NDVI-based that bare land, covering 67% of the watershed, significantly contributes to erosion despite its lower C factor. Conversely, tree-covered areas, accounting for 12%, have minimal erosion impact due to their dense vegetation. Built-up areas, covering 8%, have the highest C factor, indicating a high erosion potential. This thorough assessment aids in identifying priority areas for targeted erosion control efforts.

Keywords: soil loss, Ouringa River Basin, RUSLE, NDVI, RS, GIS.

INTRODUCTION

Coastal zones of Morocco, like many others around the world, face significant challenges due to natural and anthropogenic changes. Among the most pressing concerns is the impact of sediment transport during flood events, which can dramatically alter the structural integrity and functionality of critical infrastructures such as ports. Surface water, such as rivers and reservoirs, is essential for replenishing groundwater and acting as a significant water storage system (Al-Aizari et al., 2023). Surface water is also used for secondary purposes like generating electricity and supporting agriculture through irrigation (Renard et al., 1991; Park et al., 2011; Jarasiunas et al., 2020; Amellah and el Morabiti, 2021). However, surface water sources face significant threats due to natural processes, many of which are exacerbated by climate change (Melo, 2017).. These include increased variability in weather patterns, leading to droughts or floods, and accelerated soil erosion, which affects water quality and reduces the capacity of reservoirs and river basins to store water efficiently (Ganasri and Ramesh, 2016; Sundara Kumar et al., 2018; Yadav and Satyannarayana, 2020). These environmental challenges put additional pressure on water resources, complicating efforts to manage water sustainably (Dutta et al., 2015).

Various models have been developed to assess soil erosion rates, which are typically categorized into three types: experimental, semi-empirical, and physically process-based models. One of the most widely used models is the RUSLE, introduced by the U.S. Department of Agriculture (USDA) in 1978. RUSLE has become a key tool in estimating soil loss, particularly in erosion research and land management practices (Poesen et al., 2003; Abdo and Salloum, 2017; Gayen et al., 2020). This model uses a combination of factors such as rainfall intensity, soil type, topography, crop systems, and conservation practices to predict the amount of soil erosion that may occur in a specific area. RUSLE is an algorithm that relies on data collected from experimental plots to calculate soil erosion, especially in terms of sheet erosion (where thin layers of soil are removed) and rill erosion (the creation of small channels due to water flow). Its simplicity, combined with its ability to incorporate different variables, makes RUSLE a valuable tool for land managers and researchers to evaluate erosion risk and implement preventive measures (1978) (Wischmeier and Smith, 1978).The RUSLE model is not only useful for estimating the amount of soil loss but also for simulating the spatial distribution of soil erosion across different landscapes. By mapping how erosion varies across a given area, RUSLE allows researchers and land managers to visualize where soil loss is most severe. This spatial capability makes the model a valuable tool for understanding erosion patterns, identifying high-risk zones, and prioritizing areas for intervention (Renard et al., 1991; Yue-Qing et al., 2008). The Equation of (RUSLE) model with geospatial technology provides a powerful approach for assessing soil erosion. This method is widely used because it simplifies the process of estimating soil loss, is highly reliable, and can be applied to large areas, making it particularly useful for regional or national studies. Moreover, it's cost-effective compared to other methods. By using geospatial data such as satellite imagery and GIS, the RUSLE model can assess various factors like rainfall, topography, and land use, enabling efficient and practical soil erosion analysis in diverse geographic settings (Millward and Mersey, 1999; Zhang et al., 2010; Pradeep et al., 2015).

In 1990, the Food and Agriculture Organization (FAO) conducted a study on soil degradation in Morocco, uncovering alarming data about the state of the country's agricultural land. The study revealed that 12.6 million hectares of crops and pastures were at risk of degradation, a substantial portion of Morocco's productive land. Another FAO study from the same year focused on a specific area, known as Region B, where 40% of the land was affected by water erosion. This type of erosion significantly reduces soil quality by washing away nutrients, thereby diminishing the land's agricultural productivity. The findings emphasized the need for urgent soil conservation measures to protect Morocco's agricultural sustainability. Erosion not only reduces crop yields but also threatens long-term food security, especially in a country where agriculture plays a critical role in the economy. These studies highlighted the broader issue of environmental sustainability in the region (Benzougagh et al., 2022; Mohamed et al., 2022; Zouagui et al., 2018). Soil erosion in the Ouringa River basin, characterized by steep slopes and a semi-arid climate, poses significant challenges due to seasonal rainfall and human activities like deforestation and overgrazing. These factors intensify soil loss, diminishing soil fertility and causing sediment buildup in rivers, which impacts water quality and storage. The erosion problem threatens local agriculture and is complicated by inadequate land management and a lack of detailed data. While models like RUSLE, combined with remote sensing and GIS, have proven effective in erosion assessment, specific erosion patterns in the Ouringa basin remain underexplored, highlighting a critical knowledge gap. The current research aims to address this gap by assessing soil loss within the watersheds of the Ouringa River basin using the RUSLE model, integrated with remote sensing (RS) and GIS techniques. This approach is expected to yield a detailed spatial analysis of erosion patterns, allowing for better identification of high-risk zones. The study seeks to provide new insights into the extent and distribution of soil erosion in the Ouringa River basin, offering a foundation for implementing targeted soil conservation measures. The research also aims to improve the accuracy of erosion assessments through the combined use of RUSLE and geospatial technologies, providing a methodological framework that can be applied in similar semi-arid regions.

MATERIALS AND METHODS

Study area

The Ouirnga River basin is located in northwestern Morocco, approximately 50 km from the city of Tetouan. Geographically, it is situated between the Mediterranean Sea to the north and a mountain range to the south, which serves as a watershed for coastal waters. The region lies between latitude 35°12’36” N and longitude 4°42’0” W (Figure 1). This area covers about 1,033.4 square kilometers and is characterized by a predominantly mountainous terrain, with elevations ranging from 40 meters to as high as 2.070 meters above sea level(Amellah and el Morabiti, 2021; Brahim et al., 2020; Mohamed et al., 2022).

The Mediterranean basin experiences a prevailing semi-arid to arid climate. Based on meteor-ological data provided by the Hydraulic Basin Agency of Loukkos in Tetouan from 1981 to 2021, the average annual precipitation varies around 774.77 mm. With relatively cold winters, the average temperature reaches 1, and summers are hot with a temperature of 40, and the average annual T °C is 18.6 °C.

Data requirements

For the execution of this study, various types of data were utilized, as illustrated in Table 1.

Model of RUSLE

Overview

The RUSLE is a widely used model for estimating soil erosion, typically expressed as tons per hectare per year. It integrates several environmental and management factors that influence soil erosion rates. These factors include:

- Rainfall erosivity (R): Measures the impact of rainfall and runoff on soil loss. High erosivity means more potential for soil to be eroded due to rain. For instance, a study in Kerala, India, employed RUSLE and found that the highest

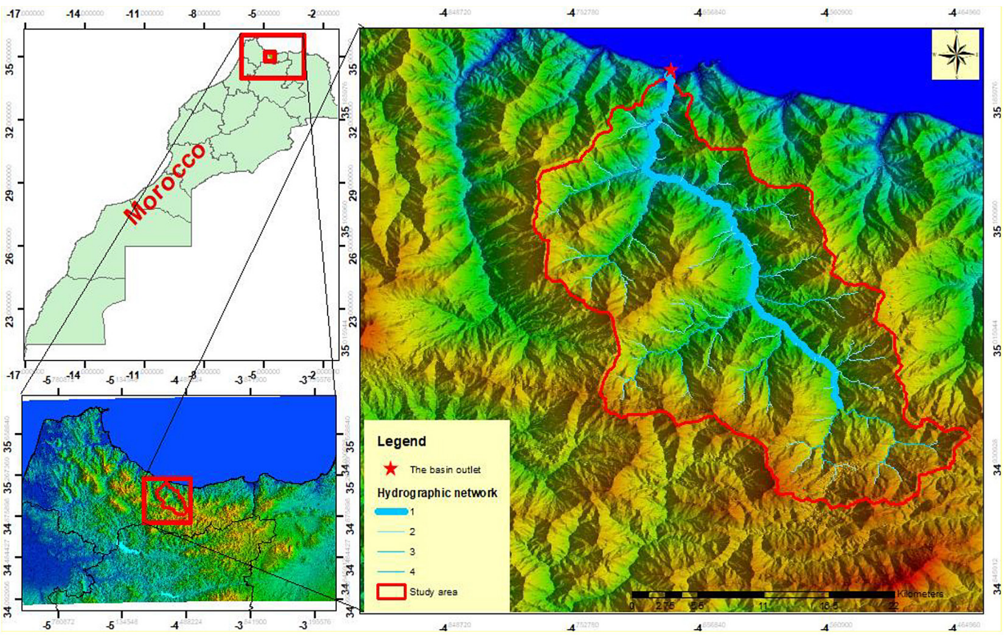

Figure 1. Ouirnga River Basin

Table 1. Data requirements

Data	Source
Digital elevation model (DEM) 30 m	Earth explorer (usgs.gov)
Climate data	https://www.chc.ucsb.edu/data/chrips
Soils data	https://www.fao.org/home/en/
Land use Land cover	Earth explorer (usgs.gov) OLI ,LandSat8

soil loss occurred in areas with high rainfall erosivity combined with steep slopes (Prasannakumar et al., 2012). To estimate (R) from the acquired climatic data, the Equation for the rainfall erosivity factor is the following Equation 1:

$$R = 1.74 \times LOG \sum_{i=1}^{n} (pi^2/p) + 129 \quad (1)$$

where: pi is the average precipitation monthly and p is average the precipitation manually.

- Soil erodibility (K): Describes the susceptibility of soil particles to detachment and transport by rainfall and runoff. Soils with higher erodibility values are more prone to erosion. For example, studies have shown that areas with specific soil types have higher K values, making them more vulnerable to erosion (Gayen et al., 2020). In this study, soil composition and soil erodibility to erosion, which are closely related to organic carbon content, were calculated according to the following Equation 2–6.

$$KrUSLE = f_{csand} \cdot f_{cl}{-si} \cdot f_{orgc} \cdot f_{hisand} \quad (2)$$

where: $KrUSLE$ – this is the soil erodibility factor for the RUSLE model, which represents the susceptibility of the soil to erosion based on its composition and other factors; f_{hisand} – this factor represent the percentage of sand particles in the soil, which can affect its ability to resist erosion.

$$f_{hisand} = \{0.2 + 0.3 \cdot exp\,[-0.256 \cdot ms \cdot (1 - \frac{m_{silt}}{100})]\} \quad (3)$$

$$f_{cl-si} = (\frac{m_{silt}}{m_c - m_{silt}})^{0.3} \quad (4)$$

where: f_{cl-si} – this factor represents the ratio of clay to silt particles in the soil, which can affect its ability to retain moisture and resist erosion

$$f_{orgC} = \left(1 - \frac{0.25 \cdot orgC}{orgC + exp[3.72 - 2.95 \cdot \mathrm{orgC}]}\right) \quad (5)$$

where: f_{orgC} – this factor represents the soil's organic carbon content, which is closely related to soil composition and can affect its ability to resist erosion.

$$f_{hisand} = \left(1 - \frac{07 \times \left(1 - \frac{m_s}{100}\right)}{\left(1 - \frac{m_s}{100}\right) + exp\left\{-5.55 + 22.9.\left(1 - \frac{m_s}{100}\right)\right\}}\right) \quad (6)$$

- Slope length and steepness (LS): Steeper and longer slopes lead to higher erosion rates as the gravitational pollution water increases its erosive power. For instance, in steep ter-rains, such as the Himalayan region, the RUSLE model indicated a strong correlation between slope steepness and increased soil erosion rates (Kalambukattu and Kumar, 2017). By calculating L and S separately, The RUSLE model has the capability to consider the impacts of slope length and steepness on soil erosion separately, and subsequently combine them in the overall LS factor Equation 7 to estimate the combined influence of topography on soil loss caused by erosion.

$$LS = (FA \times (\frac{\text{cell size}}{22.13}))^{0.4} \times \times (\frac{\sin(\text{ Slop of DEM0.01745})}{0.09})^{1.3} \times 1.6 \quad (7)$$

- Vegetation cover (C): The extent of vegetation significantly reduces soil erosion by protecting the soil surface from the impact of raindrops and reducing runoff velocity. Forested areas typically have lower C values, meaning they experience less erosion. This is evident in studies where vegetation covers substantially reduced erosion rates in various regions (Gayen et al., 2020). The Equation 8 for the cover and management factor is the following scheme Equation 8:

$$C = \mathrm{EXP}\,\{-\alpha \times \frac{NDVI}{\beta - NDVI}\} \quad (8)$$

where: C – the percentage of ground cover, which represents the proportion of soil that is covered by vegetation. NDVI: It is a remote sensing index used to estimate the density of vegetation cover. α and β: Empirical constants that control the shape and slope of the C-NDVI curve

- Conservation practices (P): Practices such as terracing, contour farming, and other soil conservation measures are represented by the P factor. Effective conservation practices can reduce soil loss significantly. A study in South China used RUSLE to show how conservation efforts decreased erosion rates over time (Ranran et al., 2013).

GIS integration and implementation

Through the utilization of GIS technology, the RUSLE model facilitates the generation of maps that offer a comprehensive understanding of regions prone to soil erosion. Through the implementation of the RUSLE Eq. using GIS algorithms and data obtained from remote sensing operations, specialized data for each factor can be generated, facilitating accurate assessments of erosion risk. To calculate the average yearly soil erosion within watersheds, the following scheme Equation 9 and (Fig. 2) are used:

$$A = R \times K \times LS \times C \times P \tag{9}$$

RUSLE is a powerful model that is widely used, and the method used in this research is shown schematically in Figure 2.

RESULTS AND DISCUSSION

The erosivity factor (R)

The R factor measures the likelihood of rainfall causing soil erosion, and is affected by its intensity, duration, and amount. (Ganasri and Ramesh, 2016). The analysis of precipitation patterns in the study area revealed no significant temporal or spatial variation in the overall amount of rainfall (Fig. 3A–D). Average annual precipitation recorded at twenty-one stations over four time periods – 1981–1991, 1992–2002, 2003–2013, and 2014–2022 – ranged from 524.29 mm to 638.59 mm, with precipitation generally increasing from coastal areas to higher elevations. However, rainfall erosivity varied significantly between stations. The R-factor values in the study area ranged from 52.32 to 144.88 MJ mm ha^{-1} h^{-1}, with the southern region exhibiting higher values, indicating a greater risk of soil loss. Compare this study with study of Esfaye et al. (2021) in the Gilgel Gibe-1 basin in Ethiopia, they found K factor values ranging from 0.032 to 0.063 t/h MJ mm^{-1}. Soils with high silt content, poor structure, and low permeability were more erodible, similar to the focus of this study on how clayey silt soils balance infiltration and runoff to modulate erodibility (Tesfaye and Ameyu, 2021). also study of Vigiak et al. (2011) the LaTrobe River catchment in Australia and found that soil erodibility ranged from 0.015 to 0.055 Mg ha h MJ mm, depending on local factors such as topsoil texture, organic content, and local knowledge of soil conditions. The study suggests that climatic factors and soil classification systems can significantly influence calculated K factor values (Vigiak et al., 2011).

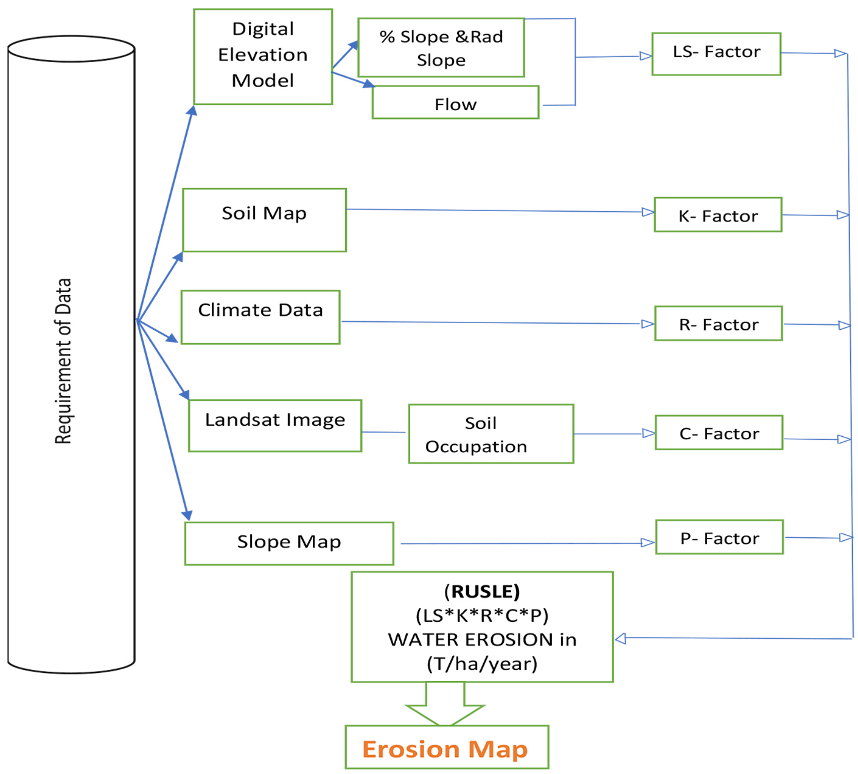

Figure 2. Schematically of RUSLE model

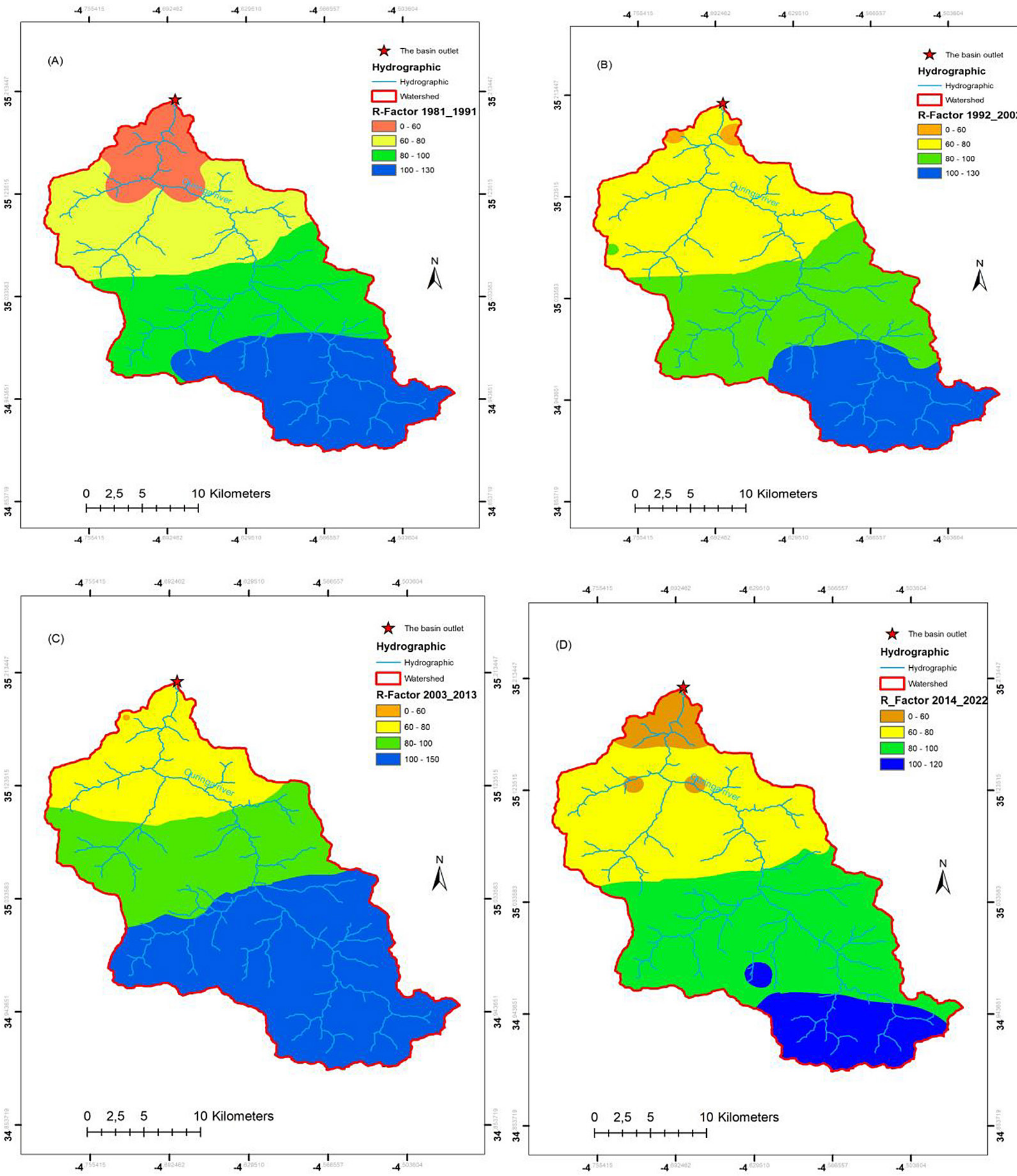

Figure 3. Map of the R-factor A, B, C, D (1981–2022) for the Ouringa River Basin

The soil erodibility (K) factor

The K-factor measures soil's susceptibility to erosion, influenced by soil properties, and is vital in USLE and RUSLE models for conservation planning (Panagos et al., 2015).

Soil erosion factor K values ranged from 0.35 to 0.35 t ha/ha/mJ/mm (Fig. 4). Medium-textured soils like silt loam have a moderate K-factor (0.25–0.4), balancing infiltration and runoff. High-silt soils are more erodible, easily detached, and prone to crusting, reducing infiltration. As a result, high silt-content soils have a higher K-factor, indicating a higher susceptibility to erosion. Consistent across many studies, soils high in silt are the most erodible, especially under conditions of low organic matter and poor soil structure, which limit infiltration and promote surface runoff. This is a common observation in Mediterranean and temperate (Tesfaye and Ameyu, 2021)

The topographic factor (LS)

The LS-factor quantifies slope length and steepness impact on erosion, derived from DEMs for USLE/RUSLE models (Fijałkowska, 2021). LS-factor values range from 0 to 1734, increasing as slopes become steeper and flow accumulation intensifies (Fig. 5). A spatial distribution map reveals that most basins have LS values between 10 and 60, with around 80% of watersheds exhibiting the highest values. The LS-factor directly

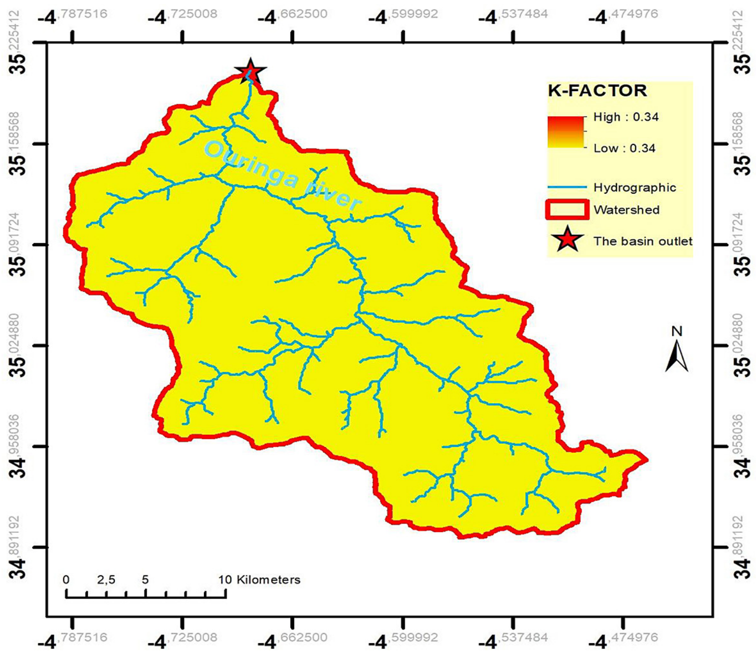

Figure 4. Map of the K factor for the Ouriga River Basin

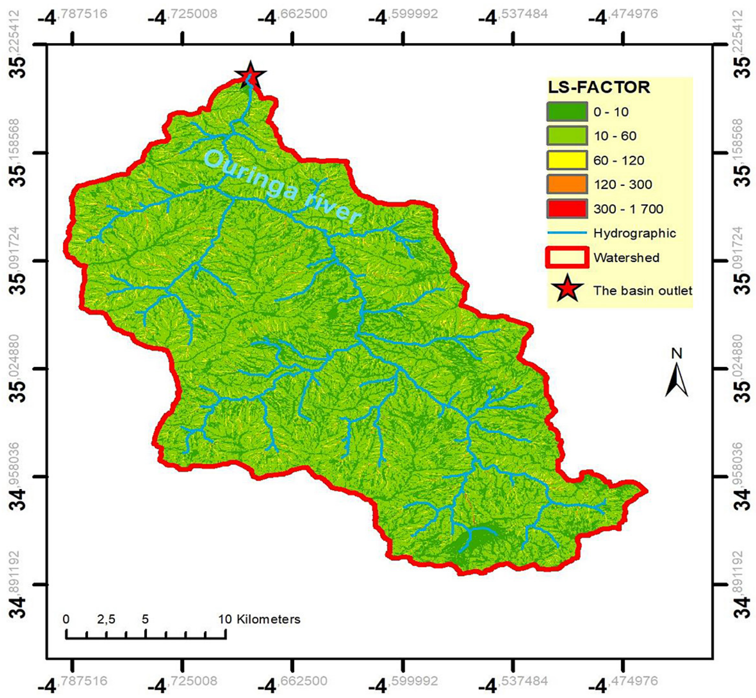

Figure 5. Map of the LS factor for the Ouriga River Basin

correlates with the topography's role in soil erosion, where longer slopes lead to higher cumulative runoff, and steeper slopes increase runoff velocity, both contributing to erosion rates. The accuracy of LS-factor estimation is highly dependent on the spatial resolution of the DEM used in its calculation (Michalopoulou et al., 2022). The highest LS values are concentrated along the watershed network, particularly in areas with complex and steep terrain, especially in the northwest. In sloped areas, rainfall accelerates water runoff, which gathers speed as it descends, carrying sediment and increasing the potential for erosion. The steeper the slope, the greater the runoff velocity and erosion risk. Steeper terrains with complex watershed networks, like those in this study, generally exhibit higher LS values, confirming the higher risk of erosion in these regions. Similar results have been observed in mountainous regions and areas with rugged terrain (Vigiak et al., 2011).

The vegetation cover factor (C)

In the Ouringa River basin, the Table 2 and Figure 6 presents the types of NDVI-based vegetation cover in the River Ouringa watershed, indicating their impact on soil erosion through C factors and detailing their area coverage in square kilometers and percentage of the total watershed area. Built-up areas have a C factor of 1.0, covering 38 km², or 8% of the watershed. These areas, with minimal vegetation, contribute significantly to soil erosion. Cropland, with a C factor of 0.28, covers 67 km², representing 13% of the area. It has a moderate impact on erosion due to agricultural activities. Bare land makes up the largest portion, with a C factor of 0.18, spanning 337 km², or 67% of the watershed. Although it has a lower erosion potential than cropland, the extensive bare land area makes it vulnerable to soil loss. Tree-covered areas, with a C factor of 0.004, cover 61 km², or 12% of the watershed. The low C factor indicates that these areas are highly effective at preventing soil erosion, thanks to the stabilizing effect of tree roots. Waterbodies and unclassified areas** have a C factor of 0.00, covering no area in the watershed, indicating they do not contribute to soil erosion.

Multiple studies employ NDVI to map C-factors and have found that areas with sparse vegetation (low NDVI) show higher erosion risks, reflected in lower C-factor values, just as your study demonstrates(Panagos et al., 2015; Tesfaye and Ameyu, 2021). Overall, while tree-covered

Table 2. Types of NDVI vegetation cover in the Ouringa watershed

Land use	C factor	Area (km)	Area (%)
Built up	1.0	38	8
Crop	0.28	67	13
Bare land	0.18	337	67
Three	0.004	61	12
Waterbody	0.00	0	0
Unclassified	0	0	0

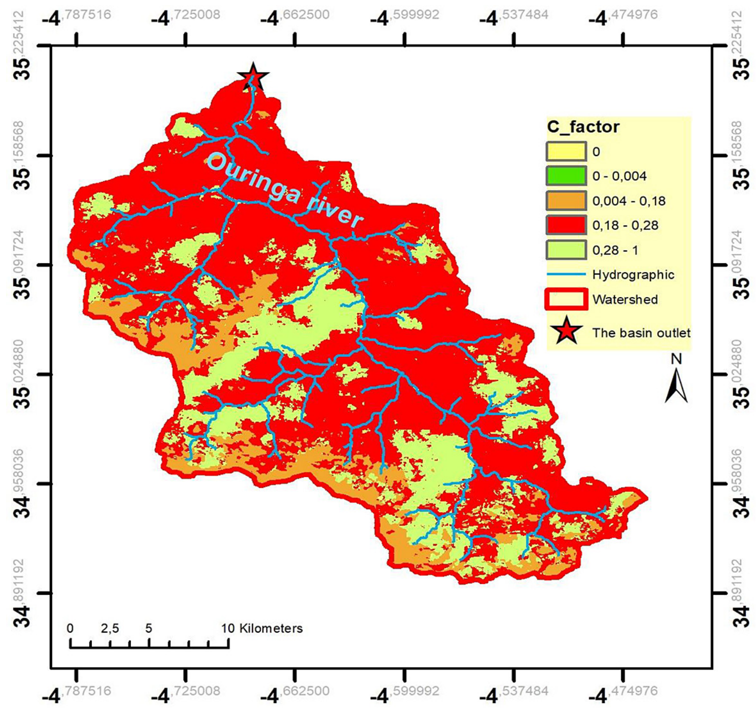

Figure 6. Map of the C factor for the Ouriga River Basin

areas provide the most protection against soil erosion, the dominance of bare land in the watershed presents a challenge for erosion control.

The factor of erosion control practices (P)

The P-factor represents the percentage of soil loss from down-slope cultivation after the adoption of conservation measures. Based on the spatial distribution map, the P-factor in the study area ranges from 0.2 to 2.10 (Fig. 7). A P-factor closer to 0 indicates highly effective conservation practices, while values near 1 reflect full protection against erosion due to the successful implementation of conservation measures. Conversely, P-factor values between 1 and 2.1 indicate areas where little to no conservation measures have been applied, leaving the soil highly vulnerable to erosion. Overall, the P-factor is a crucial parameter in the RUSLE model, as it directly reflects the effectiveness of soil conservation efforts in controlling runoff and minimizing soil loss (Cheng et al., 2018).

Evaluation of soil losses

The resulting erosion map was classified into six soil loss categories: very slight, slight, moderate, intense, very intense, and severe. These classifications help identify high-risk erosion areas, providing valuable insights for management decisions to mitigate soil loss. Based on data from 1981 to 2022 (Table 3 & Fig. 8, E, F, J, h), the study revealed six erosion hazard categories, ranging from no to low wear to very high wear.

The Table 3 shows the levels of soil erosion in the River Ouringa watershed over four distinct time periods: 1981–1991, 1992–2002, 2003–2013, and 2014–2022. It categorizes land areas based on the severity of soil loss, measured in tons per hectare annually, and highlights trends in erosion across the watershed. The data shows that the majority of the watershed, between 60% and 66%, experienced minimal soil loss, categorized as "no erosion" (0 to 100 tons per hectare annually). This indicates that most of the land in the watershed remains within acceptable soil erosion limits, suggesting relatively stable soil conditions in these areas. These areas likely benefit from either natural resilience or existing soil conservation practices. However, 20% to 23% of the land area falls into the "low erosion" category, with soil loss between 100 to 200 tons per hectare annually. While not as critical as higher erosion categories, this consistent percentage indicates areas where soil degradation could become more severe if not addressed. Additionally, about 8% to

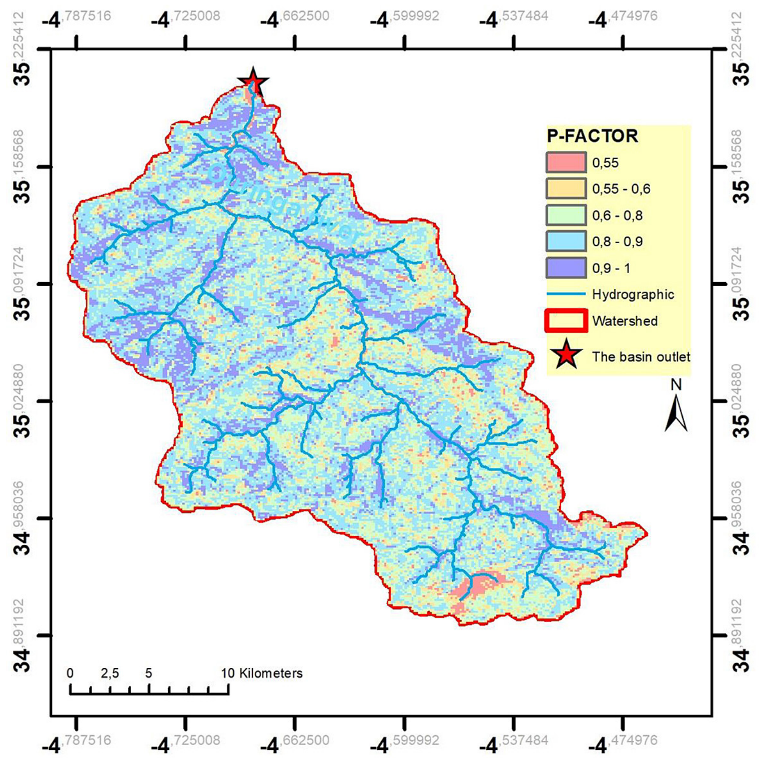

Figure 7. Map of the erosion control practices factor P for the Ouriga River Basin

Table 3. Categorization of potential soil erosion statistics

Years	ID	Classes	Erosion state	Area (KM)	%
2014–2022	1	0 to100 ton per ha	No erosion	33450.3	66
	2	100-to-200 ton per ha	Low erosion	10375.65	21
	3	200-to-400 ton per ha	Moderate	3974.67	8
	4	400-to-1000 ton per ha	Moderately high	2098.26	4
	5	1000 to 5000 ton per ha	High erosion	475.02	1
	6	Above 5000 tons per ha	Very high erosion	10.26	0.2
2003–2013	ID	Classes	Erosion state	Area (KM)	%
	1	0 to100 ton per ha	No erosion	30488.58	60
	2	100-to-200 ton per ha	Low erosion	11593.17	23
	3	200-to-400 ton per ha	Moderate	5068.44	10
	4	400-to-1000 ton per ha	Moderately high	2522.43	5
	5	1000 to 5000 ton per ha	High erosion	690.48	1
	6	Above 5000 tons per ha	Very high erosion	21.06	0.4
1992–2002	ID	Classes	Erosion state	Area (KM)	%
	1	0 to100 ton per ha	No erosion	32766.75	65
	2	100 to 200 ton per ha	Low erosion	10724.04	21
	3	200-to-400-ton per ha	Moderate	4192.02	8
	4	400 to 1000 ton per ha	Moderately high	2183.13	4
	5	1000 to 5000 ton per ha	High erosion	506.61	1
	6	Above 5000 tons per ha	Very high erosion	11.61	0.2
1981–1991	ID	Classes	Erosion state	Area (KM)	%
	1	0 to100 ton per ha	No erosion	33038.1	65
	2	100 to 200 ton per ha	Low erosion	10460.43	20
	3	200 to 400 ton per ha	Moderate	4156.2	8
	4	400 to 1000 ton per ha	Moderately high	2181.51	4
	5	1000 to 5000 ton per ha	High erosion	534.69	1
	6	Above 5000 tons per ha	Very high erosion	13.23	0.2

10% of the land experienced "moderate erosion" (200 to 400 tons per hectare annually). This level of erosion can start to affect soil fertility and productivity, and may require interventions such as reforestation or improved land management practices. Furthermore, 4% to 5% of the watershed experienced "moderately high erosion" (400 to 1000 tons per hectare), a significant level of soil loss that can lead to more serious environmental degradation. A smaller portion, about 1%, falls into the "high erosion" category, with soil loss between 1000 to 5000 tons per hectare. Lastly, although very rare (0.2% to 0.4%), some areas experienced "very high erosion," exceeding 5000 tons per hectare, posing a severe risk to land stability and productivity.

These results align with findings from the Nakhla watershed (Western Rif, northern Morocco) and the Wadi Amter watershed, which spans 300 square kilometers. Similar soil erosion patterns were observed in both regions, highlighting the consistent impact of erosion across comparable Moroccan watersheds (Issa et al., 2014; Ouallali et al., 2016; Mohamed et al., 2022). Overall, the need for targeted soil management practices in areas with moderate to severe erosion, even as a majority of the watershed experiences manageable soil loss.

CONCLUSIONS

The study successfully achieved its goal of assessing soil erosion in the Ouringa River watershed using the RUSLE model with GIS and remote sensing. The analysis provided a detailed spatial understanding of erosion patterns, highlighting that despite minor erosion in most of the area, certain zones suffer from severe losses exceeding 1000 tons per hectare annually. This research revealed previously unquantified erosion severity, especially in regions with sparse

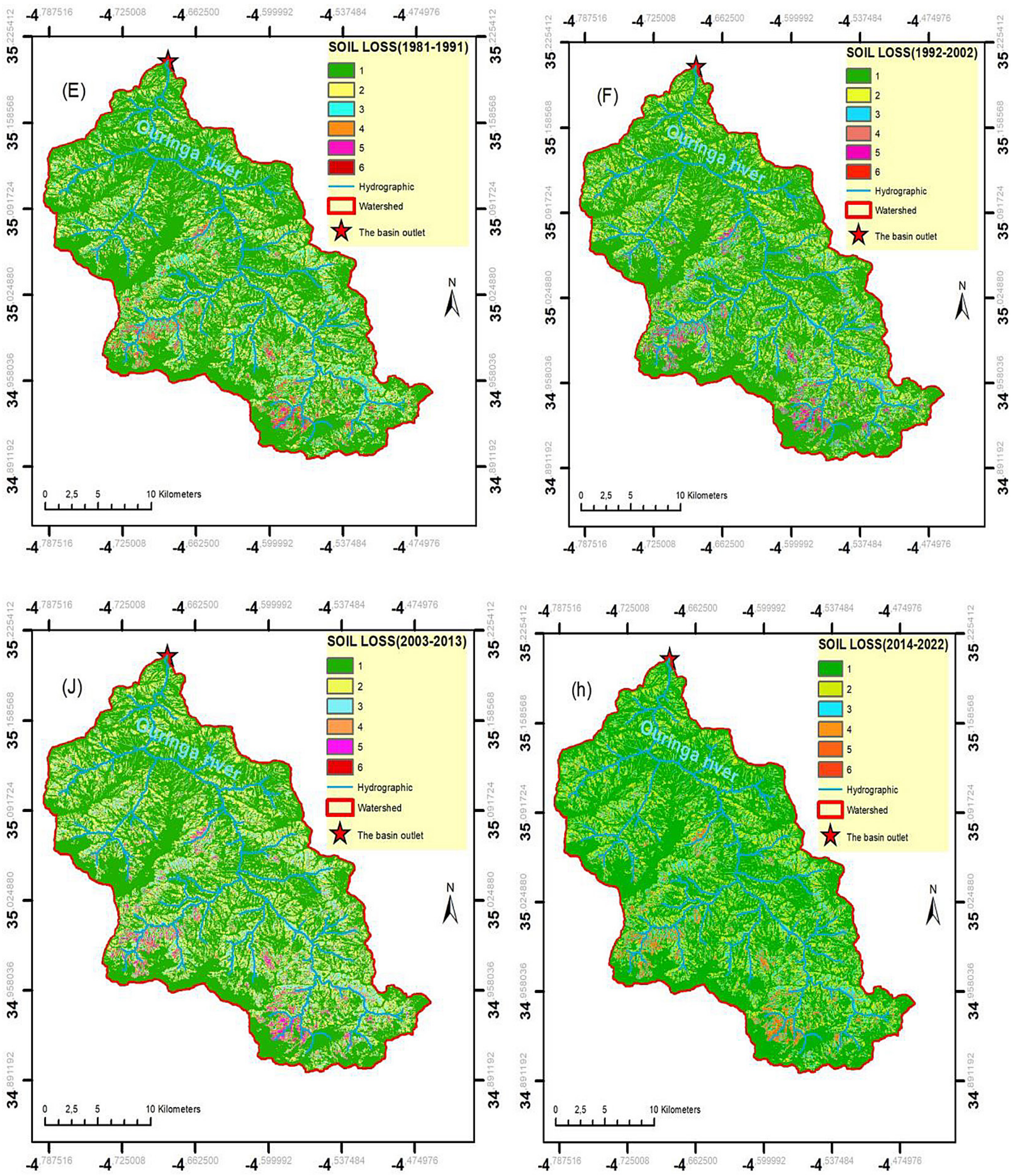

Figure 8. Soil loss maps of the Ouringa River Basin for four periods: 1981–1991 (e), 1992–2002 (f), 2003–2013 (j), and 2014–2022 (h)

vegetation cover, which earlier studies in Morocco did not capture with the same precision. By integrating NDVI-based mapping, the study filled a critical gap in linking vegetation cover to erosion dynamics. These findings open prospects for implementing targeted soil conservation practices and provide a basis for developing predictive models applicable in similar semi-arid regions.

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