Spatio-temporal Dynamics and Drivers of Soil Loss in the Poyang Lake Basin Based on GEE and Multi-Source Remote Sensing Data

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Abstract

Soil loss presents significant threats to environmental safety and agricultural security in the Poyang Lake Basin. Therefore, accurately assessing the spatio-temporal distribution of soil loss and identifying its key driving factors is essential. Utilizing the Google Earth Engine (GEE) platform and multi-source remote sensing data, this study estimates annual average soil loss and examines its spatio-temporal dynamics through the Revised Universal Soil loss Equation (RUSLE). The analysis incorporates rainfall erosivity (R factor) from CHIRPS precipitation data, soil erodibility (K factor) from OpenLandMap, topographic factors (LS factor) from DEM data, vegetation cover (C factor) from Landsat7/8 NDVI, and conservation practices (P factor) from MODIS land cover data. The results indicate significant changes in soil loss patterns from 2001 to 2020, with average annual soil loss decreasing from 13.4 t/hm² in 2001-2010 to 7.2 t/hm² in 2011-2020, reflecting a trend line coefficient of -0.5. Areas of severe erosion were identified at the confluence of the Yangtze River and Poyang Lake, particularly in Zhaisang, Lianxi, and Lushan Districts, as well as in flood-prone regions southeast of Poyang Lake and urban areas in Nanchang City. Within the same year, soil loss distribution correlates with precipitation and slope. While over 20 years, strong relationships were found between soil loss and cropland (with a Pearson correlation coefficient of 0.58) and impervious surfaces (-0.72), indicating that human activities primarily drive soil loss in the Poyang Lake Basin. The research findings align with previous studies that utilized the RUSLE model to calculate soil erosion in Poyang Lake, based on historical and geospatial data from various domestic sources. This demonstrates the effectiveness of GEE and remote sensing in assessing soil loss, providing reliable data to support the sustainable use and protection of land in the watershed.

1. INTRODUCTION

Soil loss is a widespread environmental issue globally, leading not only to the loss of soil resources but also having profound impacts on water quality, ecosystems, and agricultural production. Therefore, efficiently and accurately assessing soil loss over large spatial scales and analyzing its spatio-temporal distribution characteristics are crucial for soil loss control and conservation decision-making (Li et al., 2014). With the rapid development of GIS and remote sensing technologies, methods for monitoring and assessing soil loss are continuously evolving。 Luvai et al. (Luvai et al., 2022) categorized soil loss assessment methods into physical models, empirical models, and conceptual models based on differences in model parameters, assessment approaches, and principle.

Physical models describe the soil loss processes in watersheds by providing solutions to fundamental physical equations (Roshani et al., 2006)，Examples include the Water Erosion and Prediction Project (WEEP) developed by the USDA, the EUROSEM model designed for simulating and predicting soil loss, and the GUEST model for assessing soil loss and sedimentation processes (Flanagan et al., 1995; MISRA & ROSE, 1996; Roshani et al., 2006); Empirical models, which combine inductive logic, expert experience, and experimental results, are user-friendly, require less data and computation, and are therefore widely applied (Efthimiou et al., 2016; Merritt et al., 2003), Common examples include the Universal soil loss Equation (USLE), the Modified Universal Soil Loss Equation (MUSLE), and the Revised Universal Soil Loss Equation (RUSLE), the latter being the primary model used in this study (Renard et al., 1997; Williams & Berndt, 1977; Wischmeier & Smith, 1978), Conceptual models aim to describe the mechanisms behind water and sediment exchange within a watershed, such as the Chemical Runoff and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1980) and the Large Scale Catchment Model (LASCAM) (Viney & Sivapalan, 1999).

Since 2017, the emergence of the Google Earth Engine (GEE) platform has enabled efficient and precise processing and analysis of large-scale remote sensing data due to its powerful cloud computing capabilities (Gorelick et al., 2017). Consequently, analyzing the spatio-temporal dynamics of soil loss and its driving factors using the GEE platform and multi-source remote sensing data has become a primary method in recent soil loss research. For instance, Demir et al. utilized the RUSLE-GEE method to predict soil loss before (2020) and after (2022) a wildfire, revealing that soil loss varied with land use changes during these periods (Demir & Dursun, 2024); Islam employed GEE platform data to predict annual soil loss in Nigeria using the RUSLE model (Islam, 2022); Jodhani combined the GEE platform with the RUSLE model to quantitatively assess soil loss and sediment yield under various conditions, using GEE primarily to qualitatively generate soil loss spectral indices for assessing soil loss and land degradation in the western region of the Gujarat River Basin in India (Jodhani et al., 2023). Papaiordanidis studied the seasonal spatio-temporal variations of soil loss in the Pindos Mountains of Greece using the GEE platform and RUSLE model, estimating the correlation between seasonal components of RUSLE (precipitation and

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vegetation) and average RUSLE values (Papaiordanidis et al., 2020).

The Poyang Lake Basin holds significant importance as a vital area for fishery and food production in China, the analysis of soil loss issues within this region is of paramount significance. This study leverages the capabilities of the Google Earth Engine (GEE) platform, combined with multi-source remote sensing data, to construct the Revised Universal Soil Loss Equation (RUSLE) model. This approach facilitates an efficient and accurate analysis of the spatio-temporal dynamics of soil loss in the Poyang Lake Basin from 2001 to 2020.

By systematically identifying and evaluating the key driving factors influencing soil loss, the research aims to elucidate the complex interactions between anthropogenic activities, land use changes, and climatic conditions. The findings of this study are intended to provide a robust scientific basis for developing effective soil protection strategies and sustainable management practices in the Poyang Lake Basin.

2. STUDY AREA

Jiangxi Province has a varied topography including plains, mountains, and hills. It experiences a subtropical humid monsoon climate characterised by simultaneous rainfall and heat, with frequent heavy rainfall in summer leading to potential flooding. The centrally located Poyang Lake is the largest freshwater lake in China and serves as an important seasonal, hydrological, and throughput lake within the Yangtze River Basin. It plays a crucial role in regulating the water level of the Yangtze River, conserving water resources, improving local climatic conditions, and maintaining the ecological balance of the surrounding areas (Chronicles, 2003).

With economic development and population growth, the Poyang Lake Basin has experienced excessive land exploitation, resulting in ecological degradation. The increase in agricultural activities has exacerbated soil loss issues, which not only affects the sustainability of agricultural production but also negatively impacts the water quality and ecosystems of the lake. Given the significance of the Poyang Lake Basin in agriculture, ecological protection, and water resource management, a comprehensive study of the spatio-temporal dynamics of soil loss and its driving factors in this region holds substantial scientific and practical importance.

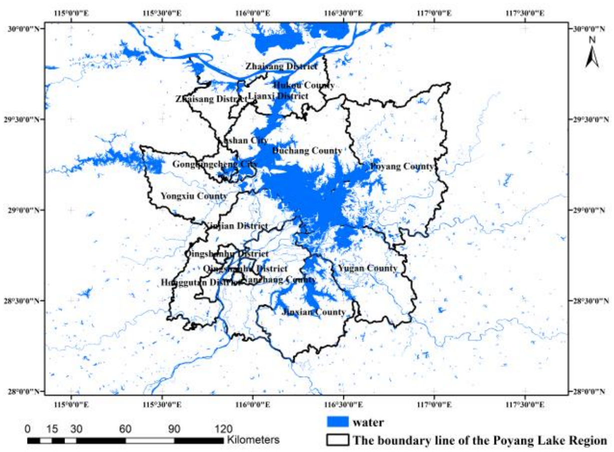

Figure 1. Study Area - Poyang Lake Basin

3. METHODOLOGY

The overall technical approach of this study is illustrated in Figure 2. First, key factors for the RUSLE model are calculated based on various geographic datasets available on the GEE platform. These factors are then incorporated into the RUSLE model to quantitatively assess soil loss in the Poyang Lake Basin. The annual average soil loss dataare then analysed to determine overall trends, and GIS spatial analysis techniques are used to identify hotspots of soil loss and their spatial distribution characteristics. Finally, correlation analysis is performed on land use/land cover (LULC) data and climate data from ERA5_Land to analyse the driving factors and identify the key elements influencing soil loss.

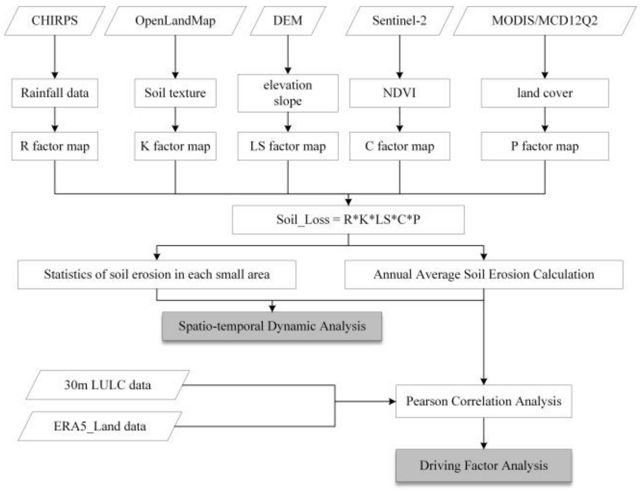

Figure 2. Technical Roadmap

3.1 Data Collection

As shown in Table 1, this study utilizes various data sources primarily derived from publicly available datasets on the GEE platform. The Rainfall Erosivity Factor is calculated based on CHIRPS precipitation data. The Soil Erodibility Factor is derived from soil texture data obtained from OpenLandMap. The Slope Length and Steepness Factor is calculated using Digital Elevation Model (DEM) data to determine slope length and gradient. The Cover and Management Factor is computed by extracting the Normalized Difference Vegetation Index (NDVI) from Landsat 7/8 data. The Support Practice Factor is derived from land cover information extracted from MODIS/MCD12Q2 data. Finally, key driving factors influencing soil loss are analyzed using land use type data from Professor Huang Xin of Wuhan University (Yang & Huang, 2021) and the ERA5_LAND dataset.

Datatype	Dataset	Time	Resol ution	Purpose of calculation
Rainfall data	UCSB-CHG/CHIRPS/PENTAD	1981	0.05°	Rainfall Erosivity Factor
Soil texture	OpenLandMap/SOL/SOL_TEXTURE-CLASS_USDA-TT_M/v02	1950-2018	250m	Soil Erodibility Factor
Digital elevation data	USGS/SRTMGL1_003	2000	30m	Slope Length and Steepness Factor
Landsat7/8	LANDSAT/LE07/C02/T1_L2 LANDSAT/LC08/C02/T1_L2	1985-2022	30m	Cover and Management Factor
Land Cover Dynamics data	MODIS/006/MCD12Q1	2001-2020	500m	Support Practice Factor

land cover dataset	projects/lulc-datase/assets/LULC_HuangXin/	1990-2023	30m	Driving Factor Analysis
Climate data	ECMWF/ERA5_LAND/MONTHLY_AGGR	1950-	1km	Driving Factor Analysis

Table 1. Data source

3.2 The RUSLE Model

The Revised Universal Soil Loss Equation (RUSLE) is a widely utilized empirical model designed to estimate soil loss rates caused by water (Renard et al., 1997). It serves as an essential tool for researchers, land managers, and policymakers in assessing soil loss risk and implementing effective soil conservation practices. RUSLE is an enhancement of the original Universal Soil Loss Equation (USLE), incorporating advancements in understanding soil loss processes and improving parameterization. The RUSLE is mathematically expressed as follows:

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

Where A represents the predicted soil loss (tons per hectare per year), R denotes the rainfall erosivity factor, K indicates the soil erodibility factor, LS refers to the slope length and steepness factor, C signifies the cover and management factor, and P represents the support practice factor.

Rainfall Erosivity Factor (R): This factor quantifies the impact of rainfall on soil loss, reflecting both the intensity and duration of rainfall events. It is typically derived from historical precipitation data and can be calculated using various methods that consider rainfall characteristics. In this paper, the relationship between annual precipitation and the R factor, as derived by Singh et al., is utilized (as shown in Equation (2)). The R factor is calculated using annual precipitation data from the CHIRPS dataset available on the GEE platform (Singh et al., 1981)。

$$R_i = 0.363P_i + 79 \tag{2}$$

Where P_i represents the average annual rainfall for the i-th year , and R_i denotes the R factor for the i-th year.

Soil Erodibility Factor (K): The K factor represents the susceptibility of soil to erosion, based on its physical and chemical properties. It is determined through laboratory analysis of soil samples or by referencing established soil databases that provide K values for different soil types. In this paper, the K Factor values are assigned based on the 12 soil categories from the b0 dataset in the OpenLandMap Soil Texture Class available on the GEE platform, utilizing the findings from the research conducted by Bouguerra et al. (as shown in Table 2) (Bouguerra et al., 2017).

value	Description	K factor
1	CI（Clay）	0.0288
2	SICI（Silt Clay Loam）	0.0341
3	SaCI（Sandy Clay Loam）	0.036
4	ClLo（Clay Loam）	0.0394
5	SiClLo（Silt Clay Loam）	0.0423
6	SaClLo（Sandy Clay Loam）	0.0264
7	Lo（Loam）	0.0394
8	SiLo（Silt Loam）	0.0499
9	SaLo（Sandy Loam）	0.05
10	Si（Silt）	0.045
11	LoSa（Loamy Sand）	0.017
12	Sa（Sand）	0.0053

Table 2. K factor in different soil texture

Slope Length and Steepness Factor (LS): This factor accounts for the influence of topography on soil loss. It is calculated using digital elevation models (DEMs) to assess slope length and steepness。This study calculates the LS factor using the 30m DEM data from the GEE platform, following the formula proposed by Wischmeier et al (Wischmeier & Smith, 1978) (as shown in Equation (3)):

$$LS = (\sqrt{L} \times \frac{0.305}{100}) \times (0.76 + 0.53 \times S + 0.076 \times S^2 \tag{3}$$

Where L represents the slope length，while S denotes the slope percentage (%).

Cover and Management Factor (C): The C factor reflects the protective effect of vegetation and land management practices on soil loss. It is influenced by the type of vegetation, its density, and the management practices employed. Therefore, it is common practice to first calculate the NDVI (Normalized Difference Vegetation Index) values based on remote sensing imagery data (as shown in Equation (4)). Subsequently, the C factor (cover and management factor) is computed using the formula proposed by Knijff et al (Knijff et al., 2000) (as shown in Equation (5))：

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{4}$$

$$C = \exp\left(-\alpha\left(\frac{NDVI}{\beta - NDVI}\right)\right) \tag{5}$$

where NIR represents the near-infrared reflectance, and RED represents the red reflectance; α and β define the NDVI curve, and α = 2 and β = 1.

Support Practice Factor (P): This factor indicates the effectiveness of soil conservation practices, such as contour farming, terracing, or the use of cover crops, in reducing soil loss. P values are determined based on the specific practices implemented in a given area. Kassie et al. proposed a method that combines the effects of topography with watershed characteristics and land use/land cover, allowing for the assignment of appropriate P factors based on different land use types and actual terrain conditions (Kassie et al., 2018). In this study, we have integrated land use types and slope to establish the P factor, with the setting principles outlined in Table 3(The values of "LC_Type1" in the MODIS/006/MCD12Q1 dataset represent different land cover types, and the specific interpretations and definitions of these distinct values are detailed in the table provided in the Appendix.):

Slope(°)	Value of "LC_Type1" in MODIS/006/MCD12Q1	P Factor
/	＜11	0.8
/	11	1
/	13	1

/	>14	1
<2	12 or 14	0.6
<5	12 or 14	0.5
<8	12 or 14	0.5
<12	12 or 14	0.6
<16	12 or 14	0.7
<20	12 or 14	0.8
>20	12 or 14	0.9

Table 3. Principles for Setting the P Factor

Based on the formulas, we take the year 2010 as an example and utilize multi-source remote sensing data to calculate the five key factors in the RUSLE (Revised Universal Soil Loss Equation). The results of these calculations are illustrated in Figure 3.

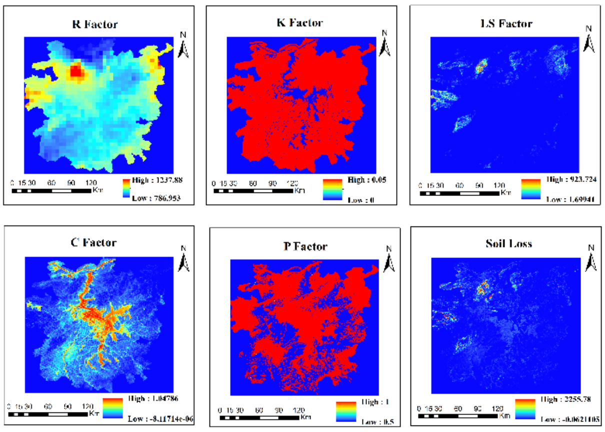

Figure 3. Results Map of Key Factors for RUSLE in 2010.

3.3 Driving Factor Analysis Methods

In the driving factor analysis, the analysis of driving factors in the horizontal spatial dimension determines the factor that has the greatest impact on soil loss in the Poyang Lake Basin by calculating the KL divergence values between the soil loss imagery and the image data of different factors. KL divergence is an asymmetric measure of the difference between two probability distributions (Kullback & Leibler, 1951). In the field of image processing, KL divergence can be used to measure the similarity between images; the smaller the KL value, the more similar the distributions of the two images are. The calculation formula is as follows (equation 6):

$$D_{KL}(P \parallel Q) = \sum_{x} P(x) \log \frac{P(x)}{Q(x)} \tag{6}$$

In the equation, P(x) and Q(x) represent the probability density functions at point x ; $D_{KL}(P \parallel Q)$ denotes the KL divergence from distribution Q to distribution P.

In the analysis of driving factors along the vertical time dimension, the Pearson correlation analysis method(Pearson, 1900) is employed to quantitatively calculate the correlation coefficients between multi-year soil loss data and the corresponding land use/land cover (LULC) data, as well as climate data such as temperature, precipitation, and evaporation during the same time period. This approach helps identify the factors that have the greatest impact on soil loss. The calculation formula for the Pearson correlation coefficient is as follows (Equation 7):

$$r = \frac{Cov(X,Y)}{\sigma_x \sigma_y} \tag{7}$$

Where $Cov(X,Y)$ represents the covariance between the independent variable X and the dependent variable Y , while σ_x and σ_y denote the standard deviations of variables X and Y, respectively. A higher Pearson correlation coefficient indicates a stronger correlation between the two variables.

4. RESULTS

4.1 Spatio-temporal Dynamics of Soil Loss

The average soil loss trends in the Poyang Lake Basin from 2001 to 2020 are shown in Figure 4, which shows significant fluctuations in soil erosion over this period. In particular, except for the years 2003 and 2010—when soil loss exceeded 20 t/hm²—the maximum soil loss in other years was limited to 15 t/hm². This pattern suggests that extreme weather events, particularly heavy rainfall and flooding, contributed significantly to soil erosion during in these years.

Following 2010, a marked improvement in soil loss conditions is evident. The average annual soil loss from 2001 to 2010 was 13.4 t/hm², while this figure decreased substantially to 7.2 t/hm² from 2011 to 2020. This reduction indicates the effectiveness of soil conservation measures and improved land management practices implemented in the region. Overall, the trend line shows a consistent decline in soil loss over the past two decades, with a slope of -0.5, highlighting a gradual yet significant improvement in soil loss conditions within the Poyang Lake Basin. This underscores the positive impact of targeted interventions aimed at mitigating soil erosion and promoting environmental sustainability. The temporal variation trend of soil erosion in Poyang Lake is consistent with the results(TAN et al., 2023) calculated using the RUSLE model based on historical data from meteorological stations in 2023 and geospatial data compiled from various domestic websites.

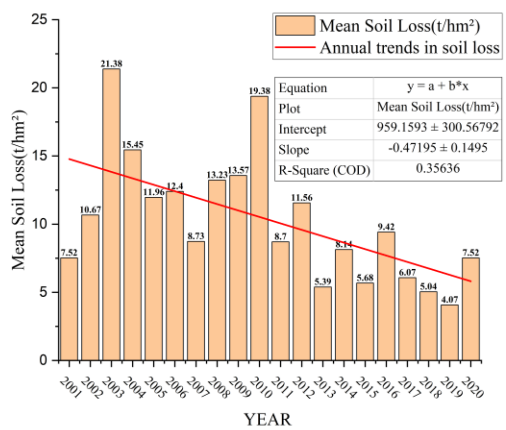

Figure 4. The average soil loss trend chart from 2001 to 2020 (the table content represents the correlation coefficient values of the trend line).

The spatial distribution of soil loss in the Poyang Lake Basin over time is comprehensively illustrated in Figure 5. Utilizing a classification system based on soil loss levels—specifically "<10, 10-20, 20-30, 30-40, >40" (measured in t/hm²)—the soil loss types within the basin are categorized into five distinct classes: Slight, Moderate, High, Very High, and Severe. This classification allows for a nuanced understanding of the varying degrees of soil erosion across the region.

Analysis of the spatial distribution of soil loss over the years reveals that areas experiencing the most severe erosion are primarily concentrated in three key locations, as highlighted in Figure 5 under "Soil Loss 2020." The first area of concern is the junction of the Yangtze River and Poyang Lake, particularly within the Zhaisang District, Lianxi District, and Lushan District. This region is characterized by its unique hydrological dynamics, which contribute to heightened erosion rates.

The second area of significant soil loss is the floodplain located to the southeast of Poyang Lake, especially at the intersections of Poyang County, Xinjian District, and Yugan County. This floodplain is particularly vulnerable to erosion due to its susceptibility to flooding and sediment displacement during heavy rainfall events.

Lastly, the urban area of Nanchang City also exhibits notable soil loss, likely influenced by urbanization and land use changes that disrupt natural soil structures. The concentration of severe soil loss in these areas underscores the urgent need for targeted soil conservation strategies and effective land management practices to mitigate erosion and protect the ecological integrity of the Poyang Lake Basin. Understanding these spatial dynamics is crucial for developing interventions that address the specific challenges faced by these vulnerable regions.

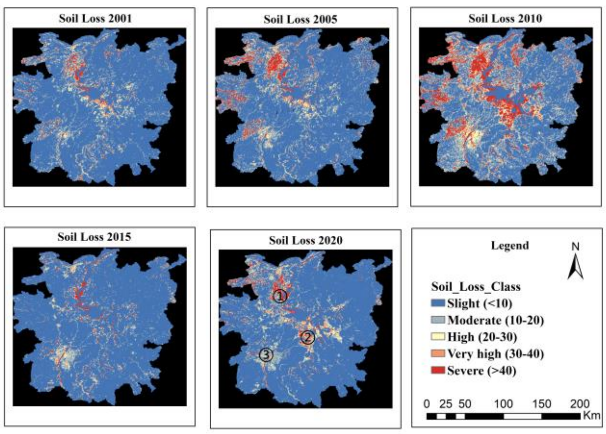

Figure 5. Soil loss Spatial Distribution Map (in 'Soil Loss 2020', ① represents the junction of the Yangtze River and Poyang Lake, ②represents the floodplain area to the southeast of Poyang Lake and ③ represents the Nanchang City)

4.2 Driving Factors Analysis of Soil Loss

This study conducts a comprehensive analysis of the drivers of soil loss, examining both horizontal spatial dimensions and vertical temporal dimensions. From a horizontal spatial perspective, the analysis uses the Kullback-Leibler (KL) divergence method to quantify the relationship between the gray-scale maps of different environmental factors and the gray-scale map of soil loss for the year 2010, as shown in Figure 6. The results show that the soil loss distribution map has the closest correlation with the R Factor (rainfall erosivity) and LS Factor (slope length and steepness) maps, both of which have the lowest KL Divergence values of 0.49. This finding hightlights the improtant role that rainfall and local slope conditions play in shaping the spatial distribution of soil loss within the Poyang Lake Basin. The strong association between these factors and soil loss highlights the importance of understanding hydrological dynamics and topographic influences in developing effective soil conservation strategies.

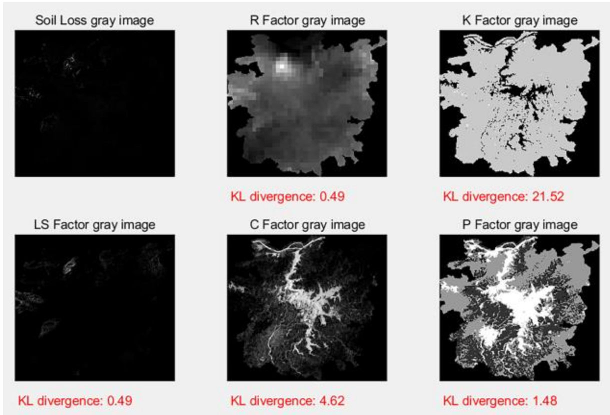

Figure 6. KL divergence between soil loss and various factors

From a vertical temporal perspective, the time series relationship between soil loss data and land use/land cover (LULC) data, as well as climate factor data, is depicted in Figure 7 and Figure 8. Analysis reveals that prior to 2010, soil loss trends were predominantly influenced by precipitation patterns, particularly highlighted by two significant flood events in 2010 that led to a dramatic spike in soil loss. These floods underscored the vulnerability of the Poyang Lake Basin to extreme weather events. However, post-2010, the correlation between precipitation and soil loss has gradually weakened. Notably, during the major flood event in 2020, soil loss exhibited only a marginal increase compared to 2019, indicating a shift in the dynamics influencing soil erosion. This suggests that other factors, such as improved land management practices or changes in land use, may have begun to play a more significant role in moderating soil loss in the region.

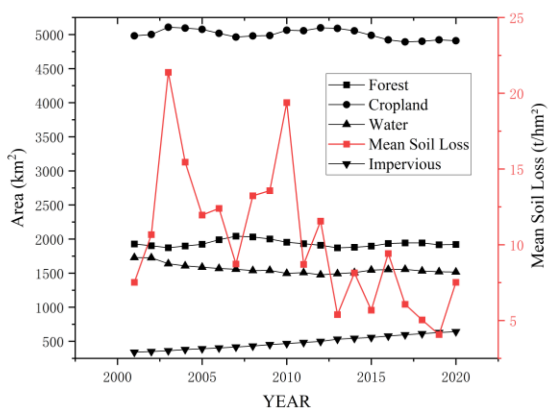

Figure 7. Temporal relationship between land use/land cover factors and soil loss

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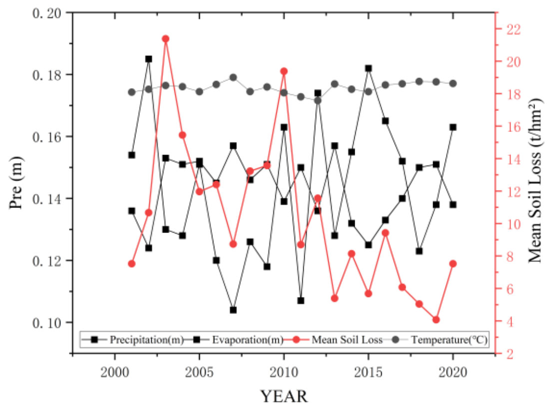

Figure 8. Temporal relationship between climate factors with soil loss

Additionally, the overall correlation coefficients between various factors and soil loss from 2001 to 2020 were calculated and visualized using a Pearson correlation heatmap, as illustrated in Figure 9. The analysis reveals that soil loss in the Poyang Lake Basin is predominantly associated with land use types, particularly cropland, which exhibits a Pearson correlation coefficient of 0.58. This positive correlation suggests that increased agricultural activities and land conversion to cropland significantly contribute to soil erosion in the region. Conversely, impervious surfaces, such as urban infrastructure, show a strong negative correlation with soil loss, with a coefficient of -0.72. This indicates that areas with more impervious surfaces tend to experience reduced soil erosion, likely due to the stabilization of soil and reduced runoff.

Furthermore, the factors of shrub, grassland, and barren land account for only 0.1% of the total area of the Poyang Lake Basin, rendering them insignificant in influencing soil loss dynamics. This analysis underscores the conclusion that soil loss in the basin is primarily driven by anthropogenic activities, particularly agricultural practices, while the influence of climatic factors appears to be relatively limited.

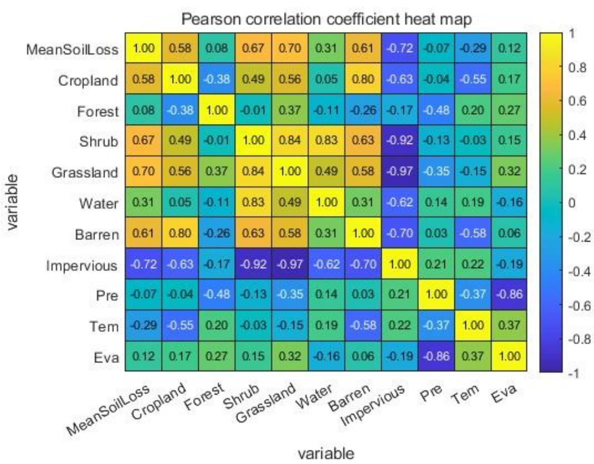

Figure 9. Driver Factor Analysis Based on Pearson's Method

5. DISCUSSION

The results of this study indicate the severe agricultural environmental problems in the region and highlitht the importance of investigating the dynamics of soil erosion in the Poyang Lake Basin. The observed decrease in average annual soil loss from 13.4 t/hm² in the period of 2001-2010 to 7.2 t/hm² in 2011-2020 suggests that conservation efforts and land management practices implemented during this time may have had a positive impact on soil preservation. However, it is essential to acknowledge the inherent limitations of this study, particularly regarding data availability, model assumptions, and potential sources of discrepancy.

One significant limitation is the reliance on remote sensing data and the availability of high-resolution datasets. While the integration of multi-source remote sensing data, including CHIRPS precipitation data, OpenLandMap soil erodibility, and MODIS land cover data, enhances the accuracy of soil loss estimations, the quality and resolution of these datasets can vary. For instance, the temporal resolution of precipitation data may not capture localized rainfall events that significantly influence soil erosion. Additionally, the spatial resolution of land cover data may not adequately represent small-scale land use changes, which can lead to discrepancies in the assessment of soil loss.

Moreover, the application of the Revised Universal Soil Loss Equation (RUSLE) involves several assumptions that may not hold true in all contexts. For example, RUSLE presupposes a uniform distribution of rainfall and does not account for the variability in soil properties across different land use types. This simplification may lead to an underestimation or overestimation of soil loss in certain areas, particularly in regions with heterogeneous landscapes. The correlation of soil loss with precipitation and slope within the same year further emphasizes the role of climatic and topographic factors; however, it also highlights the need for a more nuanced understanding of how these factors interact over time.

The identification of severe erosion hotspots, particularly at the confluence of the Yangtze River and Poyang Lake, underscores the need for targeted interventions in these vulnerable areas. The districts of Zhaisang, Lianxi, and Lushan, along with flood-prone regions and urban areas in Nanchang City, require immediate attention to mitigate the risks associated with soil erosion. These areas are likely influenced by both natural factors, such as topography and hydrology, and anthropogenic activities, including urbanization and agricultural practices. The strong relationships found between soil loss and land use types, particularly cropland and impervious surfaces, provide critical insights into the drivers of soil erosion in the Poyang Lake Basin. However, the positive correlation with cropland (Pearson coefficient of 0.58) suggests that agricultural practices may contribute to soil degradation, potentially due to tillage, crop removal, and inadequate soil management techniques. Conversely, the negative correlation with impervious surfaces (-0.72) indicates that urbanization may play a role in reducing soil loss in certain contexts, possibly due to the stabilization of soil through construction and infrastructure development. Nevertheless, this does not negate the potential for increased runoff and sedimentation associated with urban areas, which can exacerbate erosion in surrounding landscapes.

To address these limitations, future research should focus on several key areas. First, there is a need for long-term monitoring of soil loss dynamics using high-resolution temporal and spatial datasets to capture localized changes more effectively. Second, exploring the impacts of climate change on precipitation patterns and their subsequent effects on soil erosion will be crucial for developing adaptive management strategies. Additionally, investigating the effectiveness of various conservation practices over time will provide valuable insights into their long-term sustainability and impact on soil health.

Overall, this study highlights the necessity for ongoing monitoring and assessment of soil loss in the Poyang Lake Basin, particularly in light of changing land use patterns and climate variability. The insights gained from this research can inform targeted conservation strategies aimed at reducing soil erosion and enhancing agricultural sustainability. By continuing to leverage advanced remote sensing technologies and data analytics, stakeholders can develop more effective strategies to protect soil resources and ensure the ecological integrity of the Poyang Lake Basin.

6. CONCLUSIONS

In recent years, soil loss has emerged as a critical issue, exacerbated by human activities and climate change, which adversely affect agricultural practices and the ecological balance. Understanding soil loss conditions with high efficiency and accuracy is essential for effective research and intervention. This study integrates Google Earth Engine (GEE) with multi-source remote sensing data to construct the Revised Universal Soil Loss Equation (RUSLE) model, which provides a robust method for monitoring soil loss. Through a detailed case analysis of the Poyang Lake Basin, the study elucidates the temporal and spatial variations of soil loss and its driving mechanisms. The main findings are as follows:

Temporal Trends: The average annual soil loss in the Poyang Lake Basin from 2001 to 2020 exhibits a decreasing trend, with a slope of -0.5, indicating a gradual improvement in soil loss conditions over the years.

Spatial Distribution: Severe soil loss is concentrated in three primary areas: the Zhaisang, Lianxi, and Lushan Districts at the Yangtze River and Poyang Lake junction; the flood-prone southeastern regions, particularly around Poyang County, Xinjian District, and Yugan County; and the urban areas of Nanchang City.

Driving Factors: The analysis reveals that the Kullback-Leibler (KL) Divergence between soil loss distribution and precipitation and slope factors is minimal (0.49), indicating a strong relationship with these variables. Additionally, soil loss is significantly associated with cropland (0.58) and negatively correlated with impervious surfaces (-0.72), suggesting that anthropogenic activities are the primary drivers of soil loss, while climatic influences are comparatively limited.

The methodologies and findings of this research provide a valuable reference for soil loss studies in other basins and offer insights for effective soil loss prevention and watershed management, thereby supporting the sustainable development of the ecological environment.

Acknowledgements

We would like to express our gratitude to the Google Earth Engine (GEE) platform for providing invaluable data and analytical tools that have greatly enriched our research on soil loss in the Poyang Lake Basin.

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Appendix

The specific meaning of the different values of "LC_Type1" in the MODIS/006/MCD12Q1 dataset in Table 3:

LULC Value	LULC Type	Description
1	Evergreen Needleleaf Forests	Dominated by evergreen conifer trees (canopy >2m). Tree cover >60%.
2	Evergreen Broadleaf Forests	Dominated by evergreen broadleaf and palmate trees (canopy >2m). Tree cover >60%.
3	Deciduous Needleleaf Forests	Dominated by deciduous needleleaf (larch) trees (canopy >2m). Tree cover >60%.
4	Deciduous Broadleaf Forests	Dominated by deciduous broadleaf trees (canopy >2m). Tree cover >60%.
5	Mixed Forests	Dominated by neither deciduous nor evergreen (40-60% of each tree type (canopy >2m). Tree cover >60%.
6	Closed Shrublands	Dominated by woody perennials (1-2m height) >60% cover.
7	Open Shrublands	Dominated by woody perennials (1-2m height) 10-60% cover.
8	Woody Savannas	Tree cover 30-60% (canopy >2m).
9	Savannas	Tree cover 10-30% (canopy >2m).
10	Grasslands	Dominated by herbaceous annuals (<2m).
11	Permanent Wetlands	Permanently inundated lands with 30-60% water cover and >10% vegetated cover.
12	Croplands	At least 60% of area is cultivated cropland.
13	Urban and Built-up Lands	At least 30% impervious surface area including building materials
14	Cropland/Natural Vegetation Mosaics	Mosaics of small-scale cultivation 40-60% with natural tree
15	Permanent Snow and Ice	At least 60% of area is covered by snow and ice for at least 10 months of the year.
16	Barren	At least 60% of area is non-vegetated barren (sand
17	Water Bodies	At least 60% of area is covered by permanent water bodies.
255	Unclassified	Has not received a map label because of missing inputs.