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GIS AND REMOTE SENSING INTEGRATION FOR SOIL EROSION ASSESSMENT BASED ON A RUSLE MODEL IN UPNM CATCHMENT

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ABSTRACT: Soil erosion is the main threat that causes land deterioration and is one of the ultimate problems of the twenty-first century. Our study aims to determine soil erosion at the Universiti Pertahanan Nasional Malaysia (UPNM) catchment using an integrated Geographic Information System (GIS) and remote sensing (RS) utilizing the Revised Universal Soil Loss Equation (RUSLE) model. The parameters for the model are soil erosivity (R), soil erodibility (K), slope length and steepness (LS), land cover (C), and practice of land management (P), which are prepared using the varied input datasets in the ArcGIS software. The final maps model was the nearest sampled, and the soil erosion rate was calculated using an algebra map in ArcGIS. The results show that the soil erosion at the catchment is spatially varied between 0 and 99.1 t ha^{-1} yr^{-1}. The rate of soil erosion was lower than 2.3 t ha^{-1} yr^{-1}, estimated to be about 43% of the UPNM area, i.e., the highest percent of soil erosion. Moreover, the highest soil erosion is 43.5 to 99.1 t ha^{-1} yr^{-1}. Overall, the findings described the spatial pattern of soil eroded within the catchment. Thus, the proposed integrated model is useful for explaining the erosion process within the river and land system of a small area.

Keywords: Soil Erosion, Soil Erosivity, Soil Erodibility, Slope Length and Steepness, Land Management

1. INTRODUCTION

The sophisticated natural processes of sediment movement and erosion are greatly influenced by human activities such as deforestation, agriculture, and urbanization [1,2]. Erosion also leads to environmental damage through sedimentation, pollution, and increased flooding. Even though erosion is a physically active process that varies significantly in intensity and frequency globally, institutional, social, economic, and political variables also substantially impact the location and timing of erosion. The costs linked with the movement and deposition of sediment in the landscape frequently outweigh those arising from the persisting soil loss in eroding areas.

Among models that describe sediment yield and transport, empirical models like the Universal Soil Loss Equation (USLE) [3] and Revised Universal Soil Loss Equation (RUSLE) [4,5] have been extensively utilized in several spatial scales in different environments worldwide [6]. These empirical models are frequently criticized for exerting unrealistic presumptions on the physical characteristics of the catchment system, ignoring the heterogeneity of the catchment characteristics and input parameters, like soil types and rainfall. Moreover, they neglect the system of catchment nonlinearity essential [7]. Nevertheless, RUSLE is extensively used and the easiest to implement, mostly for large-scale basins. RUSLE is especially helpful in distinguishing the sources of sediment production.

RUSLE measures erosion in different land-use trends and plans for conservation. Physical modeling and information are combined with other in-situ datasets to determine how much sediment has been washed away to better help with conservation plans. RUSLE is an empirical model used to determine how much soil is lost annually at the catchment scale and describe soil erosion. Since the spatial distribution of soil erosion must be considered, remote sensing (RS) and Geographic Information Systems (GIS) are used a lot with RUSLE because of the amount of data needed and its ability to handle this type of data [4].

GIS is a system and framework for creating, managing, analyzing, and mapping data. It combines data into a map, integrating location information, such as where things are, and a wide range of interesting data. It also provides a framework for mapping and inquiry [8]. GIS applications assist users in obtaining examples and determining spatial context and linkages. GIS permits a large number of data, regardless of their source or unique configuration, to be overlaid on top of each other on a single map. A few projects have modeled a GIS software integrated with RS to automate the assessment of erosion potential [9-11].

This research aims to calculate the soil erosion at the UPNM catchment by adapting an empirical model integrated with GIS and RS. A distributed

RUSLE formulation was exerted to simulate soil erosion at the catchment. Overall, the results show that this study provides decision support for the managers of river basins about where the best management practices can be implemented effectively and at a low cost.

2. RESEARCH SIGNIFICANCE

Integrating GIS and remote sensing for soil erosion assessment based on a RUSLE model in the catchment is a valuable approach. Combining GIS and remote sensing makes it possible to analyze and evaluate soil erosion patterns and factors within the catchment area. GIS allows the collection, analysis, and visualization of spatial data, such as topography, land use, and soil characteristics. Remote sensing, on the other hand, involves acquiring satellite data or aerial imagery. This integration provides valuable insights for land managers and policymakers in understanding the severity of soil erosion in the catchment.

3. METHODOLOGY

This section discusses the methodology for determining soil erosion and explains the method that is relevant to the objective of this research. Data collection with relevant parameters was conducted after the location was identified. RUSLE is an erosion model intended to predict normal soil loss that tracks various land uses within the frameworks.

3.1 Study Area

The project was conducted at UPNM, located about 5 kilometers from Sungai Besi city, and encompasses an area of roughly 2.0 km^2 (Fig. 1) at 3°03"01.2"N and 101°43"28.8"E. It is characterized by a topography with elevations ranging from 51 m at the lowest point to 196 m at the higher point (Fig. 2). The main soil types in this catchment are tropical acrisols with significant clay build-up, high weathering, and leaching. Soil is low-fertile and sensitive to erosion, especially due to agriculture [2]. The catchment has deciduous and evergreen trees. There are 33% undisturbed forests and some steep slopes. The rainy season is from May through October, with annual rainfall averaging 80% to 90%. The dry season begins in November and continues till April. The average annual rainfall is 2000 mm, with a maximum of 4000 mm.

This project was conducted in a neighborhood where students reside and carry out their academic routine. The study area is mostly made up of a specific type of hillside and a sizable lake covering a sizable portion of the study area. Moreover, there is an area primarily comprised of a student housing complex. The students engage in daily activities, such as eating in the cafeteria, using the pool, visiting the library, and attending classes.

Fig.1 The UPNM catchment area (Source: Google Map, 2022)

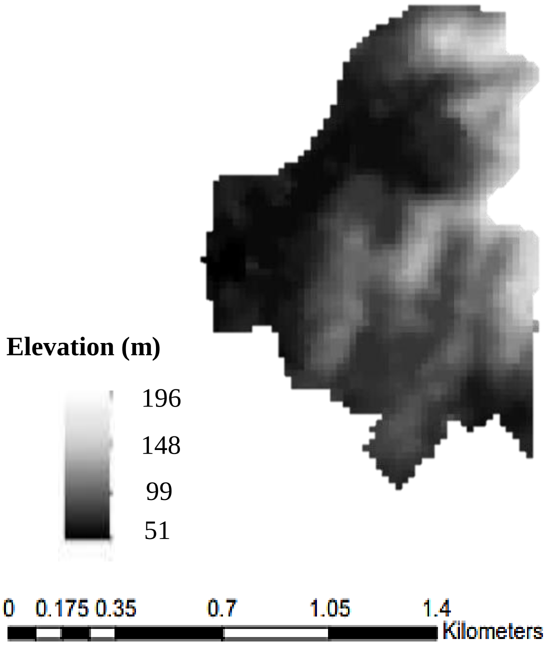

Fig.2 The elevation map

3.2 Data Sources

Table 1 shows the data sources used for this research. All satellite images were downloaded from the Earth Explorer website of the United States Geological Survey (USGS), and the framework reprocessed the Digital Elevation Model (DEM) to identify the UPNM catchment and generate slope using ArcGIS.

Table 1 Principle data and various factors in the RUSLE model

Data	Source
DEM	USGS
Landsat 8	USGS
Soil database	Harmonized World Soil Database (HWSD) (FAO)
Rainfall data	UPNM weather station
C Factor	Landsat 8
K Factor	HWSD
P Factor	Aster DEM
LS Factor	Aster DEM

A Landsat 8 satellite image at 30 m spatial resolution covering the study area captured in 2021 was used to classify the land cover to determine the land cover factor in the RUSLE model. In addition, the soil database was downloaded from the Harmonized World Soil Database (HWSD). It was used to define the erodibility factor. The rainfall data were collected from the UPNM weather station in the catchment. Rainfall data for the year 2021 was used to determine the R factor.

3.3 RUSLE Factor

RUSLE and ArcGIS compute the soil loss over the UPNM area and consider all six critical elements. Among the characteristics are soil erodibility, erosivity due to rainfall, steepness and length of slope, land cover, and support practice. The equation is as follows:

$$A = R \times K \times LS \times C \times P \quad (1)$$

where A denotes the rate of soil erosion (t ha^{-1} year^{-1}), R represents erosivity of soil factor in unit MJ mm ha^{-1} h^{-1} year^{-1}, K is the erodibility factor (t ha ha^{-1} MJ^{-1} mm^{-1}), C is a component that reflects the practice management of land cover, P is a dimensionless factor representing the effects of conservation practices, and LS is the dimensionless topographic factor composed of the length-steepness of slope factors.

3.4 Erosivity Factor (R)

The R factor indicates an erosive force at a particular period of rainfall. The factors considered are the total amount, intensity, and seasonal distribution of the precipitation. Equation (2) is used, where P indicates an annualized average rainfall in millimeters, and R is expressed as unit MJ/mm/ha/hr/yr.

$$R = 0.562 \times P - 8.12 \quad (2)$$

3.5 Erodibility Factor (K)

Soil erodibility determines how prone surface materials or soil particles are to separation and movement due to runoff and rainfall inputs [12]. The soil characteristics affect this variable. Equation (3) relates to soil characteristics and erodibility, and is used as the nomograph for computing the K factor of the soil series [6].

$$K = \frac{2.1M^{1.12}(10^{-4})(12-OM)+3.25(S-2)+2.5(P-3)}{(100\times0.317)} \quad (3)$$

where M stands for the particle size parameter defined above, and K is the erodibility factor. M = (silt% + sand%) × (100 – clay%). OM represents the percent of organic matter, S is the soil structure code, and P is the permeability code.

The soil particles least likely to erode are known as aggregated soils because they have gathered together and, thus, are more erosion-resistant. The shape file of the soil map uploaded as a layer to ArcGIS was used to calculate the K factors. The map of the soil attribute table was modified by introducing a new K value by editing the attribute view in the edit menu. The K value factor for silty sand is 0.23 to 0.30 [13].

3.6 The C Factor

Table 2 shows the C factor for this study.

Table 2 C Factor [14]

Land use type	C Factor
Orchard	0.20
Rubber	0.25
Mangroves	0.36
Forest	0.03
Road and utility	0.01
Bare land	1.00
Livestock area	0.25
Vegetable and garden	0.38
Coconut	0.20
Palm oil	0.20
Mine and Ex-mine	0.01
Paddy	0.01
Residential	0.15
Mix crop	0.25
Grass / long coarse grass	0.30
Waterbody	0.01
Tea	0.25
Water	0.00
Short grass	0.04
Built up	0.07

The C map factor was generated by categorizing

Landsat-8 satellite data from a global land cover map for the present area. Then, this map is included in ArcGIS to create a C factor map. By editing the attribute table, C factors were created similarly to K factors. Before creating the C factor, the C factor was modified by editing a new field below the attribute table. As indicated by the appropriate band for this satellite information, the information from distant detection was digitalized in the ERDAS software.

3.7 LS Factor

The steepness-length slope factor was calculated independently or together to create an index (LS). There are a few ways to calculate it, depending on the unit decisions and other available data. Thus, several empirical relations were utilized to establish this component. The steepness and length in each slope polygon (S) produced from the map may be used to measure LS. Below is an equation utilized for the present application:

$$LS = \left(fac \times \frac{30}{22.1}\right)^{0.5} \times (0.065 + 0.045 \times S + 0.0065 \times (S \times S)) \tag{4}$$

where *LS* represents the combined steepness-length slopes factor, *fac* is flow accumulation, and *S* represents the slope gradient in percent. The LS factor over the UPNM catchment was calculated using ArcGIS 10.8. The cumulative length, degree, and direction of the slope were calculated using DEM. Then, the LS factor was automatically determined using ArcGIS.

3.8 Support Practice (P) Factor

A specific site soil loss can be managed using support practice factor (P) and two other management factors. The DEM is accustomed to preparing slope data. The P value was assigned in line with the slope classes. Table 3 was used when the area was divided according to the slope classes.

Table 3 P factors for different agricultural management practices [15]

Slope (%)	P value
0 - 5	0.1
5 - 10	0.12
10 - 20	0.14
20 - 30	0.19
30 - 50	0.25
50 - 100	0.33
All	1.0

Then, the assigned value was categorized and changed to vector maps. The slope map was rasterized in ArcGIS. The present P factor value is between 0 and 1 [3,15], where values closer to 0 indicate excellent management practice. Values closer to 1 indicate no efforts have been made to conserve soil.

3.9 Determination of Soil Erosion

RUSLE was employed to determine the annual soil loss rate (A), expressed in t ha^{-1} yr^{-1}. The ArcGIS raster calculator function calculated the R, K, LS, C, and P parameters to forecast an average annual soil loss rate at UPNM.

4. RESULTS AND DISCUSSION

After calculating the possible soil erosion, the contrastive elements of the RUSLE equation were computed and spatialized.

4.1 R Factor

The R factor was distributed spatially (Fig. 3) within the UPNM catchment representations. The mean R factor of 3.32 MJ m^{-2} indicates that the catchment was exposed to rainfall. The intensity and length of the rainfall greatly impact the R-factor. Soil erosion increases as the rainfall erosivity factor rises [15], especially during the first two phases of soil erosion (detachment and transportation).

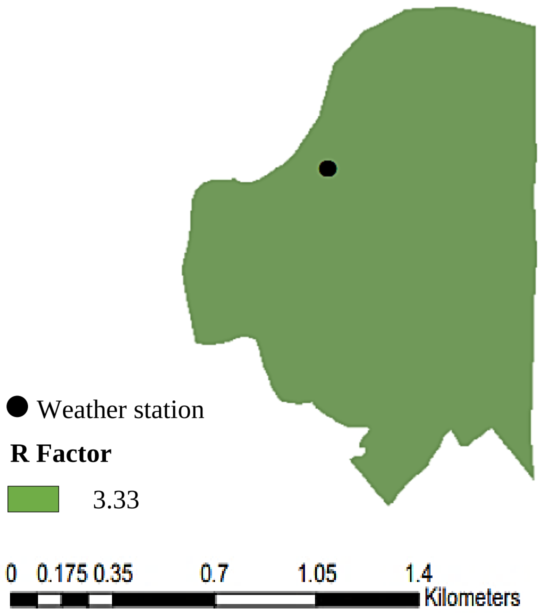

Fig.3 Rainfall erosivity map

Moreover, more water evaporated into the air when the temperature increased, leaving plants and soil with less moisture, causing dry periods to last longer than they would if temperatures were cooler. Therefore, the likelihood that precipitation will cause soil erosion is reduced, as is the capacity of runoff to transport eroded soil.

4.2 K Factor

K measures how easily soil erodes on average (t MJ^{-1} h mm^{-1}). Figure 4 shows the K factor map. The K factor value in this study is 0.30. This value does not fluctuate much due to the uniformity of the various soil types and properties [16,17].

Certain soil types are vulnerable to severe erosion because of their physical composition. Permeability, soil texture, and concentration of organic matter influence erodibility [12]. The particles of soil that are least likely to erode are known as aggregated soils because they are gathered together and, thus, are more erosion-resistant. The soil particles that are most easily eroded are very fine sand and silt [2].

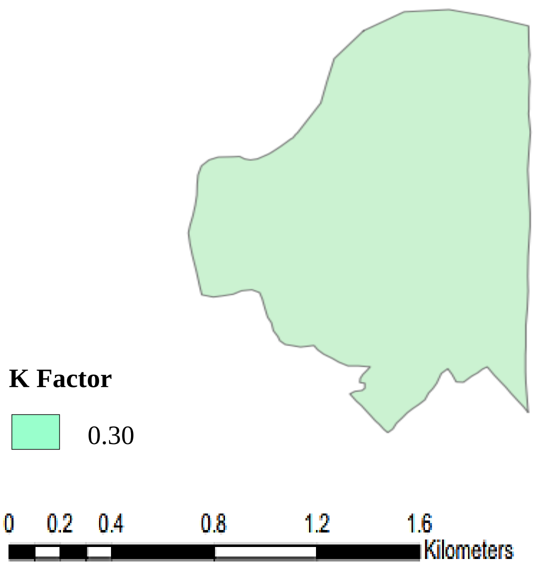

Fig.4 K factor map

The soil map of the UPNM catchment in raster format for 2021 was downloaded from FAO [16]. The attribute table was modified to include an additional K value under the edit menu. Later, the layer of soil map was included in ArcGIS before K factor maps were generated.

4.3 C Factor

Figure 5 shows the C factor map generated for 2021. For this study, the C factor value for the UPNM catchment is within 0.0001 to 1. The factor C values vary between 0 and 1 and indicate the crop-vegetation management effect on soil erosion rates.

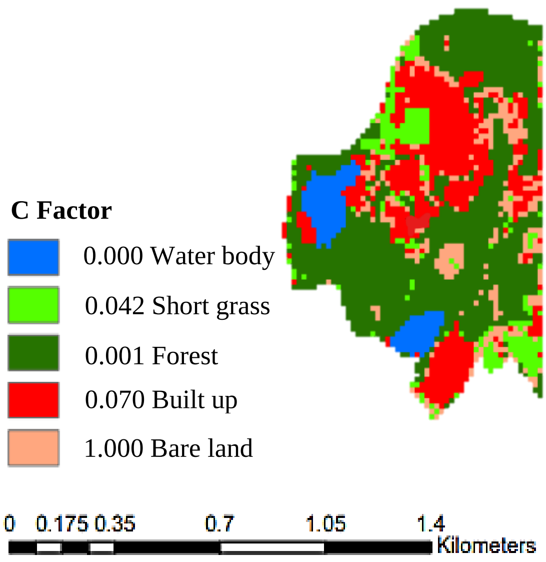

Fig.5 Cover management factor 'C'

C values were taken by Landsat 8 and created in ArcGIS 10.8 software. Several field verifications helped satellite image interpretation. The land cover in the UPNM catchment was categorized into five: water, built-up area, bare land, forest, and short grass. By editing the attribute table, C factors were created using the same process as K factors.

4.4 LS Factor

Figure 6 shows the LS factor map for UPNM catchment.

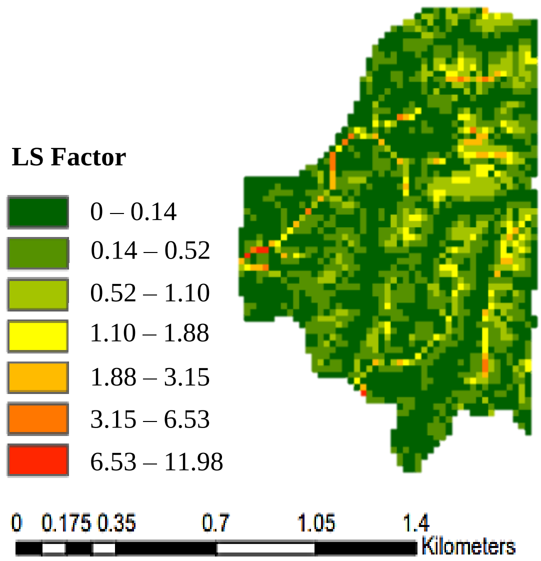

Fig.6 LS factor map

The LS component of RUSLE accounts for the soil erosion influenced by topography by incorporating the effects of a length-steepness slope factor. The LS factor was within the range of 0 to 11.98, covering 60% of the catchment area, and had a low average value, reflecting the lower elevation of the area. In addition, the futsal court area has a high LS value in the range of 3.15–6.53 due to the significant high flow accumulation in the area. Gemilang Hill and Cloud Tree residences have a medium LS value of 0.52–3.15.

4.5 P Factor

Figure 7 shows that P, the factor for practice-support management, varies from 1.0 to 0.55. The greater the support-practice management, the lower the P value. P constitutes the impacts of practices that diminish the rate and volume of runoff water, which diminishes the quantity of eroding. Subsequently, it might lower the cost of soil loss. This measures the percentage of lost cropland soil affected by certain support practices, comparable to the loss effect by upslope and downslope tillage. The P factor of the area near the vicinity was assumed to be low (0.55) to high (1) for the entire study region. A specific area can determine the P factor value. Fig. 7 shows that the red area has a higher P factor value because buildings and constructions are in the area, which contribute to erosion. The green color indicates natural land with no construction and building that has a lower P factor value.

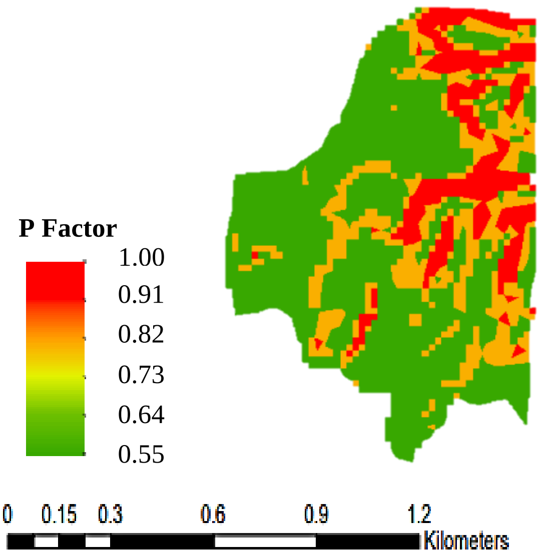

Fig.7 Support-practice factor ‘P’

4.6 The Potential Soil Erosion (A)

Figure 8 presents the RUSLE model's estimation of the annual mean of soil eroding across the UPNM catchment as measured using Eq. (1). It shows the soil loss distribution for five categories of soil loss value. The soil erosion yield class is divided into five qualitative categories: low soil erosion (0.0-2.3 t ha^{-1} yr^{-1}), moderate soil erosion (2.3-7.7 t ha^{-1} yr^{-1}), high soil erosion (7.7-18.7 t ha^{-1} yr^{-1}), very high soil erosion (18.7-43.5 t ha^{-1} yr^{-1}), and extreme soil erosion (43.5-99.1 t ha^{-1} yr^{-1}).

Our findings demonstrate that low classes are dispersed throughout the UPNM catchment region. The low slope steepness ranges from 0% to 5.98%. The low class takes up 43% of the study area. These soils, which include sand and clay, are more permeable and very resistant to the effects of runoff [2]. The protective function of forests and organic plant cover is also a major factor in moderate class erosion. In this area, the moderate class comprises up to 36% of the bottom part and some of the upper part. The high class, comprising 16.1%, was dispersed within the middle part and is close to Bukit Gemilang. Furthermore, very high and extreme soil erosion classes in terms of soil loss are 4.2% and 0.7%, respectively, which is to be expected given the presence of grasslands and a larger average annual rainfall distribution. Additionally, the soil type is a high concentration of silt and sand, making it easily detached by runoff [18,19]. In this instance, synthesizing the many classification criteria for soil erosion yields an accurate assessment of the potential area [20].

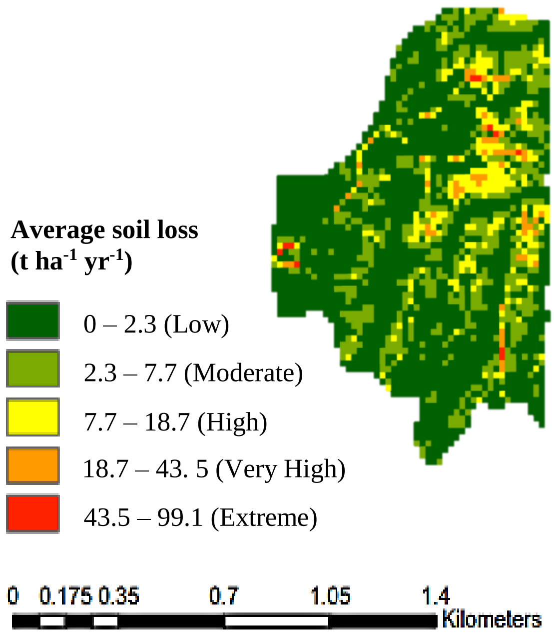

Fig.8 Average soil loss (t ha^{-1} yr^{-1})

5. CONCLUSION

This study has established an estimated surface erosion using an empirical modeling originating in precipitation data, distribution of GIS data, and RUSLE model. The presented approach offers a practical methodology to predict soil erosion in the UPNM watershed while appropriately considering land use management practices. Then, a river networking routing method that assumes the distribution of geomorphology erosion was transported with a time scale linked with the RUSLE model to assess soil loss.

Our findings show how soil erosion has been distributed spatially within the catchment. The highest amount of soil erosion was near the middle part due to steep slopes and high records of annual rainfall. The following can assist in locating places with significant soil erosion that require precedence management of basin for soil-water conservation.

The method described here demonstrates a suitable method for locating and evaluating severe soil erosion at a local catchment, such as UPNM. The results of soil erosion are crucial in assessing exchanges and patterns in sediment load in the water catchment. It may be used at UPNM and other minor catchments.

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