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Identifying Erosion-Prone Areas in the Mackinaw Watershed Using Geospatial Techniques

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Abstract: *Soil erosion manifests globally as major land degradation driven by hydrological forces such as wind and torrential water downpours frequently across the globe. Mapping areas highly vulnerable to erosion effectively informs soil conservation efforts and bolsters watershed management initiatives remarkably well nationwide. Over the years, a variety of models have been applied to better estimate soil erosion rates and predict sediment yield with greater precision. In this study, we used an empirical model to measure the average yearly soil loss. The Revised Universal Soil Loss Equation (RUSLE) was utilized to pinpoint areas within the Mackinaw Watershed catchment which are very susceptible to erosion. The model integrates with Geographic Information System tools analyzing spatial distribution of involved parameters deeply within various contexts. Soil loss rates in tons per hectare per year were used to categorize catchment area into different severity classes of erosion in the area of study.*

Keywords: *Soil, erosion, environment degradation, GIS, remote sensing, Mackinaw Watershed*

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1.0 Introduction

Erosion in the soil is a major problem in our environment, influencing the environment's life, the safety of water, and how effective the land is for farming (Lal, 2001; Kumarasiri et al., 2022). Factors such as the texture of the soil, the amount of organic matter, and how the land is being used are majorly responsible for deciding the rate of erosion, as stated by Kosmas et al. (1997). Desheng et al., (2002) classified soil disaster as either man induced, or nature induced. Erosion marks the first pattern of a sediment disaster, which is why constant monitoring of soil loss is important (Syum et al., 2025). To accurately evaluate erosion, it is important to comprehend the locations of soil loss (Karaburun, 2010). Due to both natural and man-made factors, soil particles are separated, moved, and deposited during soil erosion (Lal, 2001). Differences in land use, weather patterns, urbanization, and landscape are some of the main factors contributing to global warming (Boardman, 2006). However, due to the complexity of the numerous hydro-geological processes, estimating soil loss in watersheds remains challenging (Singh et al., 2008).By identifying areas within a watershed that are most prone to erosion, decision-makers can prioritize interventions, optimize land management strategies, and mitigate environmental impacts (Uniyal et al., 2020; Lemma et al., 2019). The RUSLE is frequently used to forecast soil erosion in various global locations. To determine where intervention is most needed and to estimate the amount of soil that will be lost, numerous specialists have attempted predictive modeling. According to Karaburun (2010), a major factor in validating erosion risk assessments is the model selection and the factors it incorporates, with Renard et al. (1997) providing a comprehensive guide on its application for conservation planning. This methodology has proven effective in varying environmental conditions and is commonly integrated with GIS technologies to enhance soil erosion predictions (Agboola & Hashemi, 2024). GIS integration improves spatial analysis by incorporating variability in topography and land use, as demonstrated in Wall et al. (2002), who applied RUSLE in Canada. Cooper (2011) and other studies highlight how soil erosion contributes to silt accumulation in water bodies, which deteriorates water quality. It has been demonstrated that using Geographic Information Systems (GIS) greatly increases the accuracy of forecasts of soil loss (Agboola et al., 2024). Furthermore, assessing sediment transport dynamics requires an understanding of how precipitation patterns and the R-factor in the RUSLE model interact.Effective soil erosion management practices are vital for mitigating soil loss, as highlighted by studies such as Pelton et al. (2012), who emphasized the importance of accurate estimation of the slope length factor (LS) in RUSLE for hilly terrains. This precision is crucial for improving the accuracy of erosion predictions in the current project, which seeks to refine the P factors. Kim (2006) has out a thorough analysis of erosion of the soil in the San Marcos Sub-basin in Central Texas using GIS and the RUSLE model. In order to calculate soil loss precisely, the study converted important environmental and soil factors into raster datasets. The findings highlighted the spatial diversity of erosion throughout the basin by showing that the northwest section of the watershed had the highest rates of erosion. In addition, regional studies on hydrology and sediment dynamics in small catchments conducted by Haan et al. (1994) offer important insights into regional sediment transport processes and erosion patterns. The research underscores the importance of precise soil erosion estimation for effective sediment management and river system health, ultimately contributing to better environmental management practices.

Empirical regression equations are still often employed to forecast soil erosion and sediment output because of their ease of use and low data requirements (Parveen and Kumar, 2012). The Universal Soil Loss Equation (USLE) and its analogs, the Modified USLE (MUSLE) and Revised USLE (RUSLE), are one of the most common models used worldwide (Adetoro and Akanni, 2018). In order to anticipate and mitigate erosion, these empirically based models have been thoroughly validated in agricultural watersheds worldwide (Zhang & Nearing, 2005).

In watershed systems, erosion contributes to the loss of topsoil, sedimentation of rivers and lakes, and reduced water quality, which in turn affects agriculture, biodiversity, and local communities (Muleta et al., 2021; Issaka and Ashraf, 2017; Pimentel, 2006).Using a GIS-based erosion risk model that incorporates several datasets, this study maps and evaluates soil erosion risk zones in the Mackinaw Watershed, Illinois. This research is crucial for directing efficient sediment control and watershed management techniques since, despite its environmental significance, no previous work has been done to measure or anticipate soil erosion within this watershed. The study's primary goals are to: (i) identify erosion-prone regions to assist in the development of targeted plans for soil management and preservation;(ii) use ArcGIS and the Revised Universal Soil Loss Equation (RUSLE) to create a predictive soil erosion map for the Mackinaw Watershed; (iii). To identify zones within the watershed that are at the greatest risk of soil erosion based on slope, rainfall, land use, and soil characteristics and produce the spatial erosion risk map. (iv) To effectively combines theoretical frameworks with practical applications as a valuable resourcefor understanding and addressing soil erosion issues.

1.1 Geographical setting of the Mackinaw Watershed

The Mackinaw Watershed, located in central Illinois, covers some counties across central Illinois which includes parts of McLean, Woodford, Tazewell, Ford, and Livingston.In the 295,000-ha Mackinaw Watershed, agriculture makes up around 90% of the land use (Lemke et al., 2011). Based on the topography, the Mackinaw Watershed exhibits gently rolling terrain, typical of the central Illinois landscape. The geological history of the watershed has been shaped by glacial activity during the Pleistocene epoch, which deposited layers of loess, till, and outwash materials across the region. (Weibel and Nelson, 2009). The watershed is defined by stream valleys, wetlands, and flat plains. The Mackinaw River itself flows westward, eventually emptying into the Illinois River near Pekin, Illinois.

2.0 Materials and Methods

Data collection: The first step involved gathering relevant data for the RUSLE parameters, These include the following: slope length and steepness (LS), soil erodibility (K), rainfall-runoff erosivity (R), land cover management (C), and conservation measures (P).

Historical precipitation data were obtained to calculate the R factor, The datasets used and their corresponding sources are described in detail in Table 1. Data from land cover photography and satellite-based digital elevation models were used to compute the LS and C factors. Soil surveys were also used to determine the types of soil and determine the K values that corresponded to them. The NAD 1983 (2011) UTM Zone 16N projected coordinate system was used for all spatial analyses.

Table 1: The study's data source

Data	Spatial Resolution	Year	Source
DEM	30m	2023	USGS
Land-Use/Land-Cover	30m	2023	NLCD
Soil	30m	2023	ESRI - SSURGO
Rainfall	800m	1991-2020	PRISM
Stream		2023	USGS - NHD

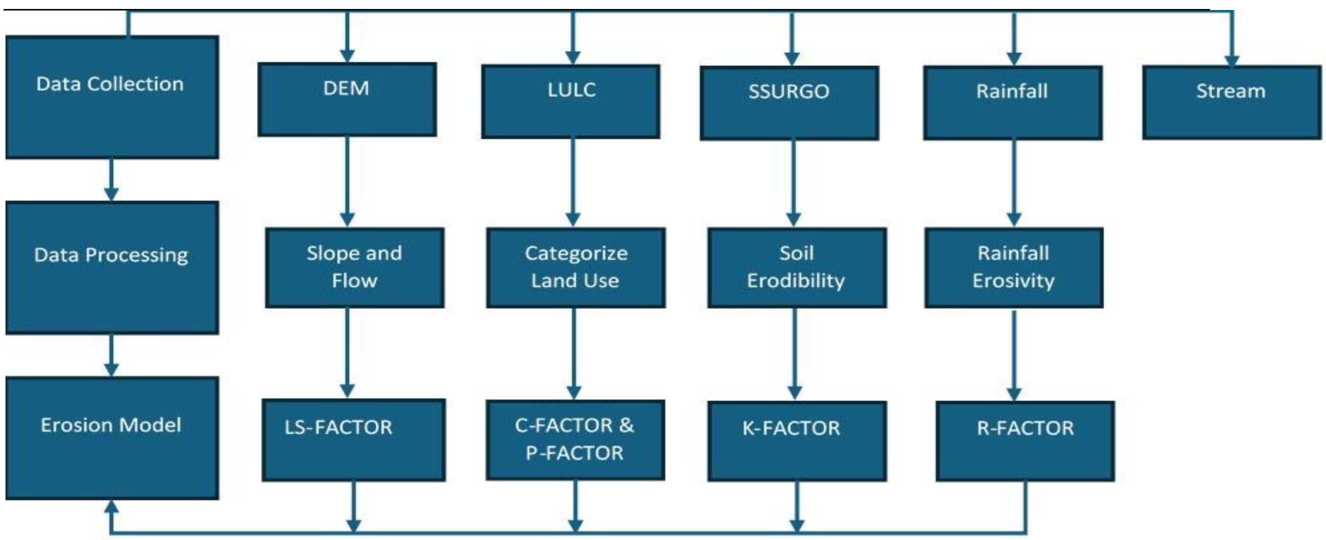

Fig. 1: The flow chart for the study area

This research, following the methods laid out by Wall et al. (2002) and Renard et al. (2017), used both the Universal Soil Loss Equation (USLE) and its updated version, the Revised Universal Soil Loss Equation (RUSLE), to estimate the mean yearly loss of soil. The RUSLE model figures out soil erosion in tons per acre each year with a straightforward equation: $A = R \times K \times LS \times C \times P$, which was first introduced by Wischmeier and Smith back in 1978.

In this equation, A - represents the calculated soil loss per unit area,R - represents the rainfall and runoff factor,K - represents the soil erodibility factor,L-S - represents the slope length and steepness factor

C - represents the cover and management factor

P - represents the support practice factor

Each of these parameters is an Calculated estimate of specific conditions that affect the mean yearly soil loss at various places (Luvia et al., 2022). Hence the calculated erosion values derived from the RUSLE can differ from location to location based on prevailing weather and landscape conditions. The methodology for this study involved several key steps, including data collection, parameter estimation, and GIS analysis.

2.1 GIS Analysis

R-Factor: This discusses the rainfall erosivity factor, known as the R-factor, which was calculated using average yearly rainfall data collected from 1991 to 2020. In the area studied, yearly rainfall varied between 926 mm and 983 mm. To improve spatial analysis, the rainfall map data was adjusted from an original resolution of 800 meters down to 30 meters. As stated by Freimund and Renard (1994), the R-factor for U.S. regions with mean annual rainfall over 850 mm can be estimated using the following equation: R-factor = $587.8 - 1.219P + 0.004105P^2$ ($r^2 = 0.73$). An R-factor raster layer was created by applying this equation to the typical yearly precipitation data using the GIS raster calculator tool.

K-Factor: For better spatial analysis, rainfall map data was re-sampled from 800m to 30m spatial resolution. The mean yearly precipitation information from 1991 to 2020, which ranged from 926 mm to 983 mm in the area of research, was used to compute the rainfall erosivity factor (R-factor). The R factor was determined by using the Renard & Freimund (1994) equation, which is based on areas with yearly rainfall above 850 mm: $R = 587.8 - 1.219P + 0.004105P^2$ ($r^2 = 0, 73$). This process was carried out within a GIS (ArcGIS 10.1) environment using raster calculator converting Typical yearly rainfall (mm/year).

LS-Factor: The topographic factor was gotten by combining the length of the slope (L) and slope steepness (S) into a single LS-factor, thanks to the Osmel formula. To calculate this LS-factor, we used the USPED (Unit Stream Power Erosion and Deposition) method. This approach involves a raster-based analysis of flow buildup and the slope of the watershed, as detailed by Pelton et al. (2012).

C and P Factors: The effects of land cover and use on soil vulnerability to water erosion is explained by the land-cover management factor. According to Parveen and Kumar (2012), it is the proportion of loss of soil from croplands to that from bare (tilled) plots that are compared under identical meteorological conditions. The P factor was used as a constant value of 1, as a straight row farming is carried out in the region. The P was obtained as per method of Parveen and Kumar (2012).

Using the RUSLE formula ($A = R \times K \times LS \times C \times P$), the soil loss estimate was completed, a raster calculation to mean loss of soil for each cell within the Mackinaw watershed. The raster layer output was further reclassified, using ranges defined by Parveenand Kumar (2012).

3.0 Results and discussion

The result showed the R factor map produce (Fig. 2), K-Factor map (Fig.3), LS Factor map (Fig. 4), C and P- Factors maps (Fig. 5 and 6), respectively in the area of research.

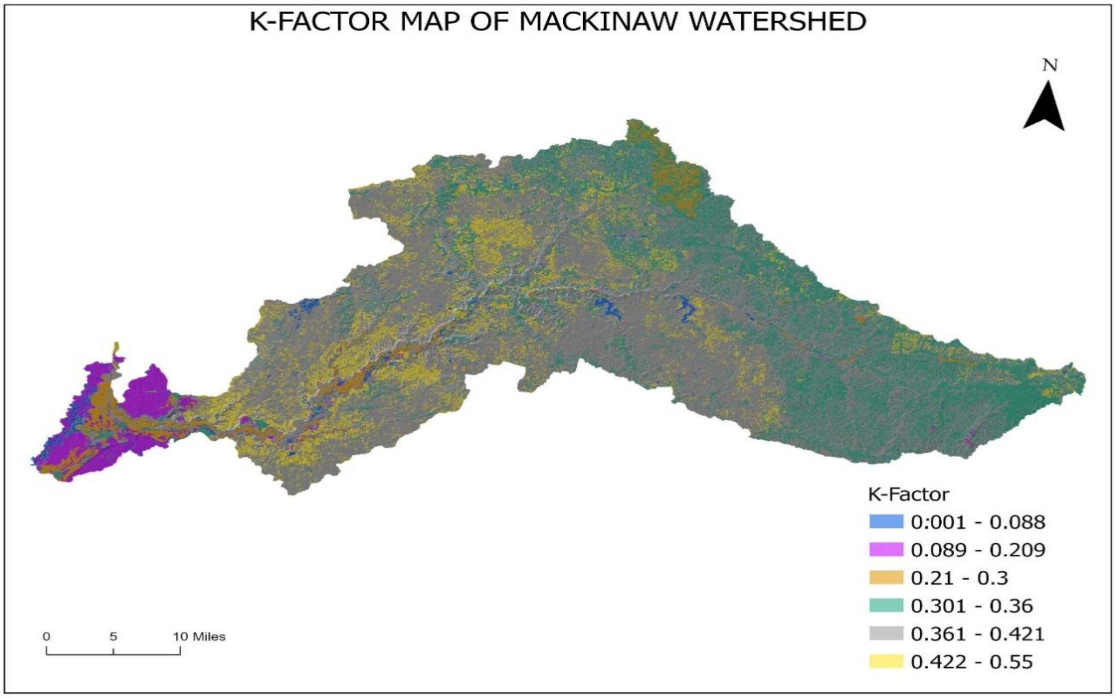

Fig.1: The K-Factor map

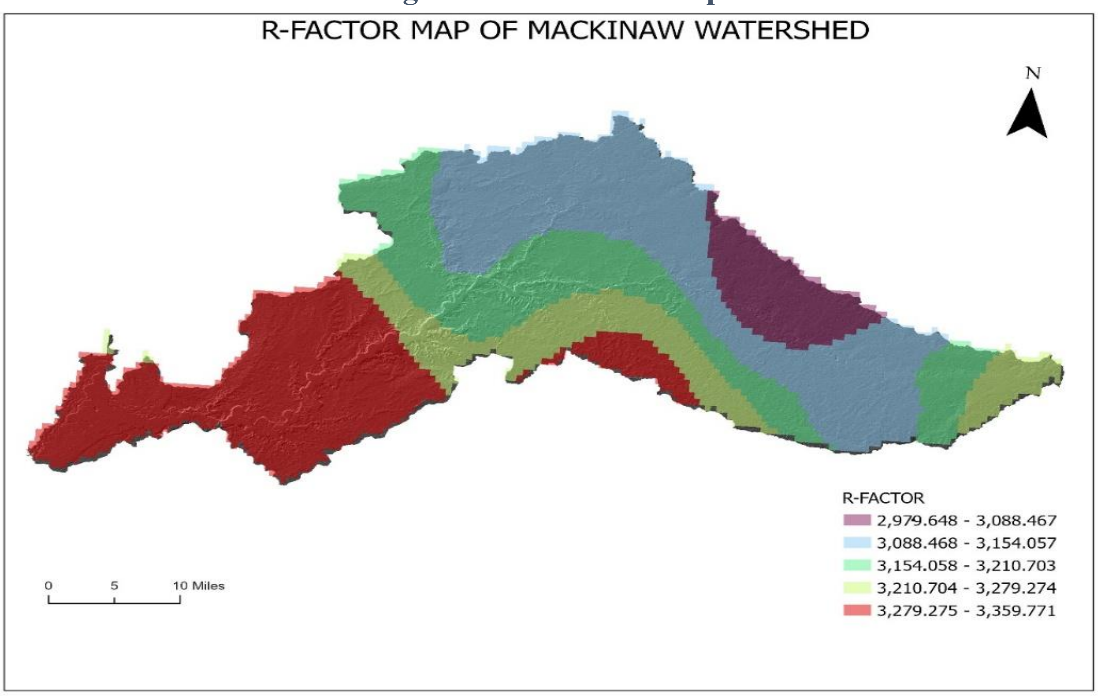

Fig. 2: displaying the R-Factor map

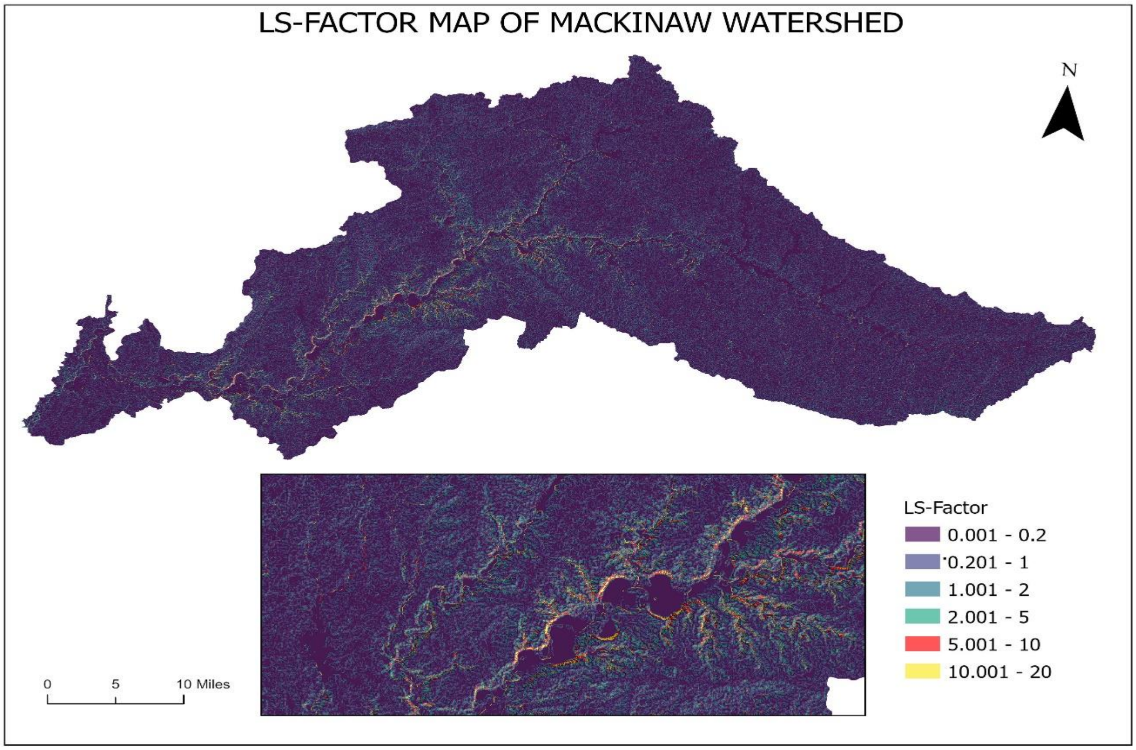

Fig. 3: LS-Factor map

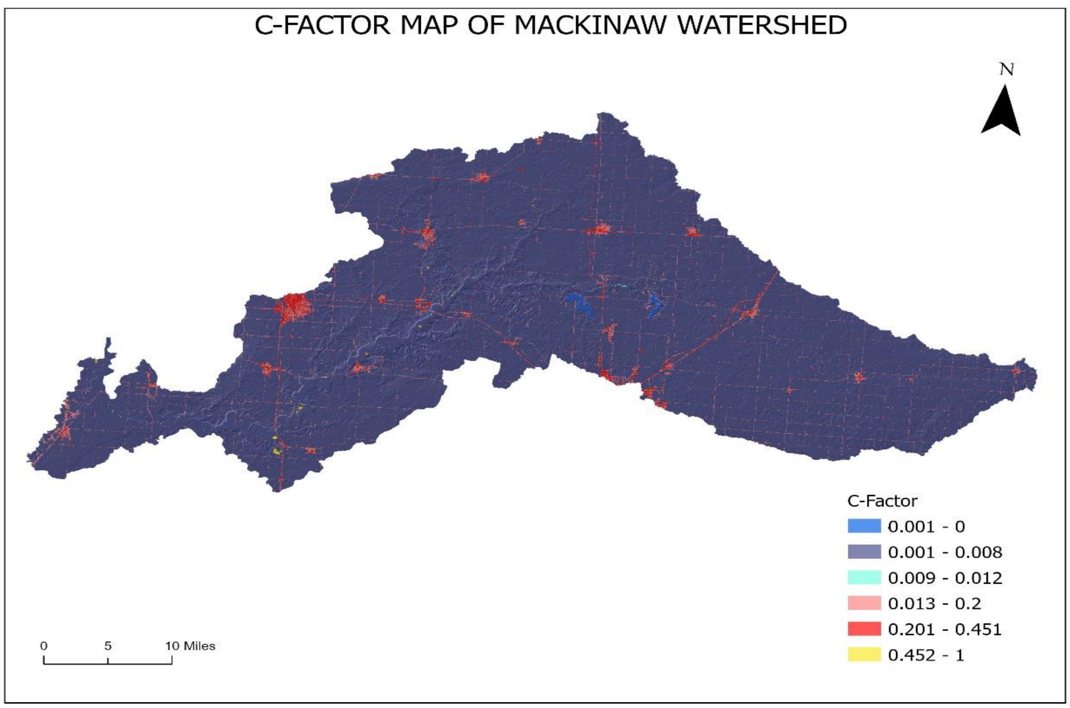

Fig. 4: C-Factor Map

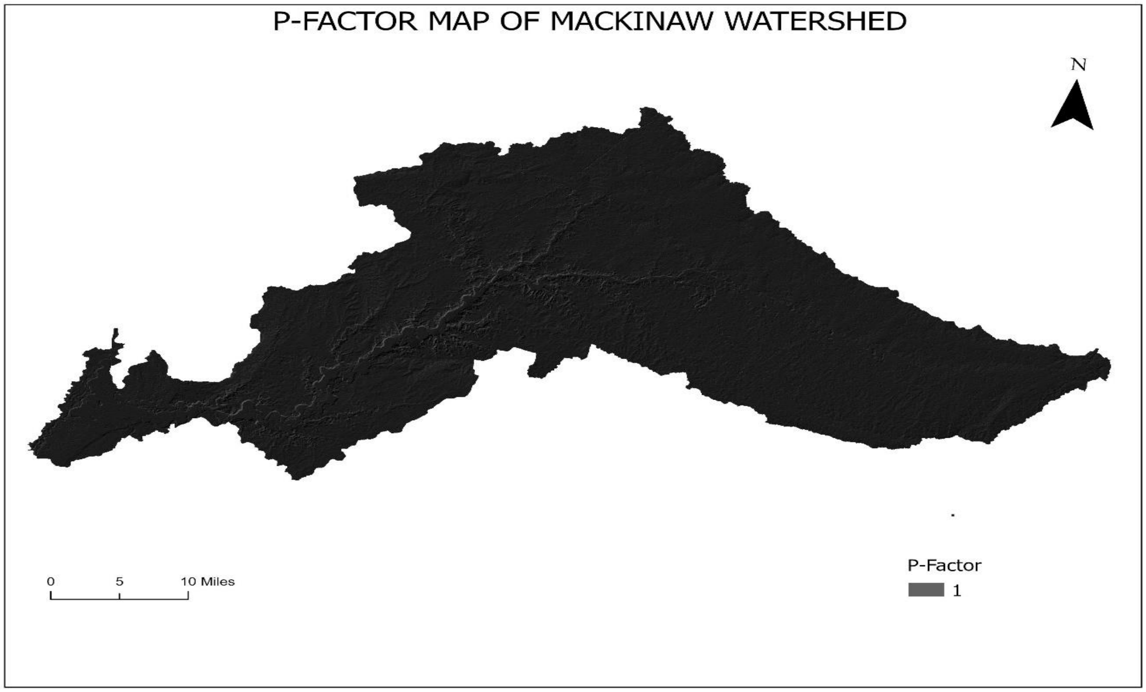

Fig. 5: P-Factor Map

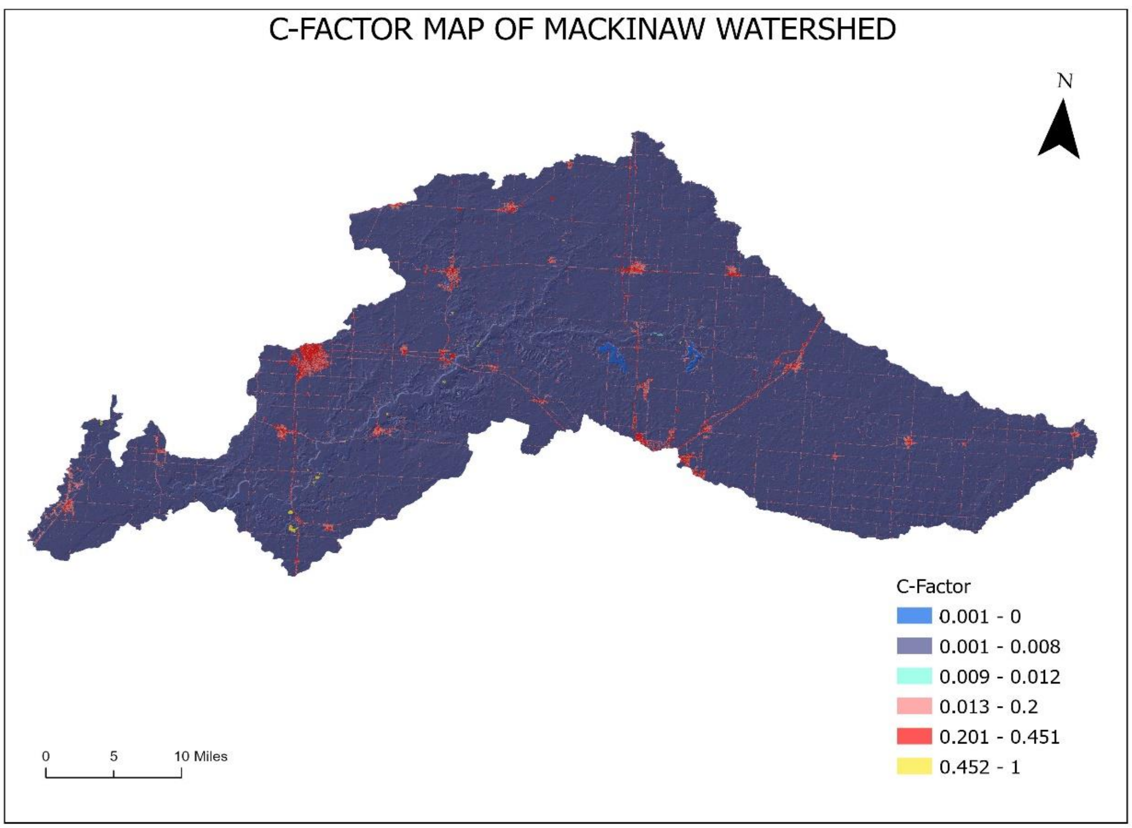

Fig. 2: C-Factor Map

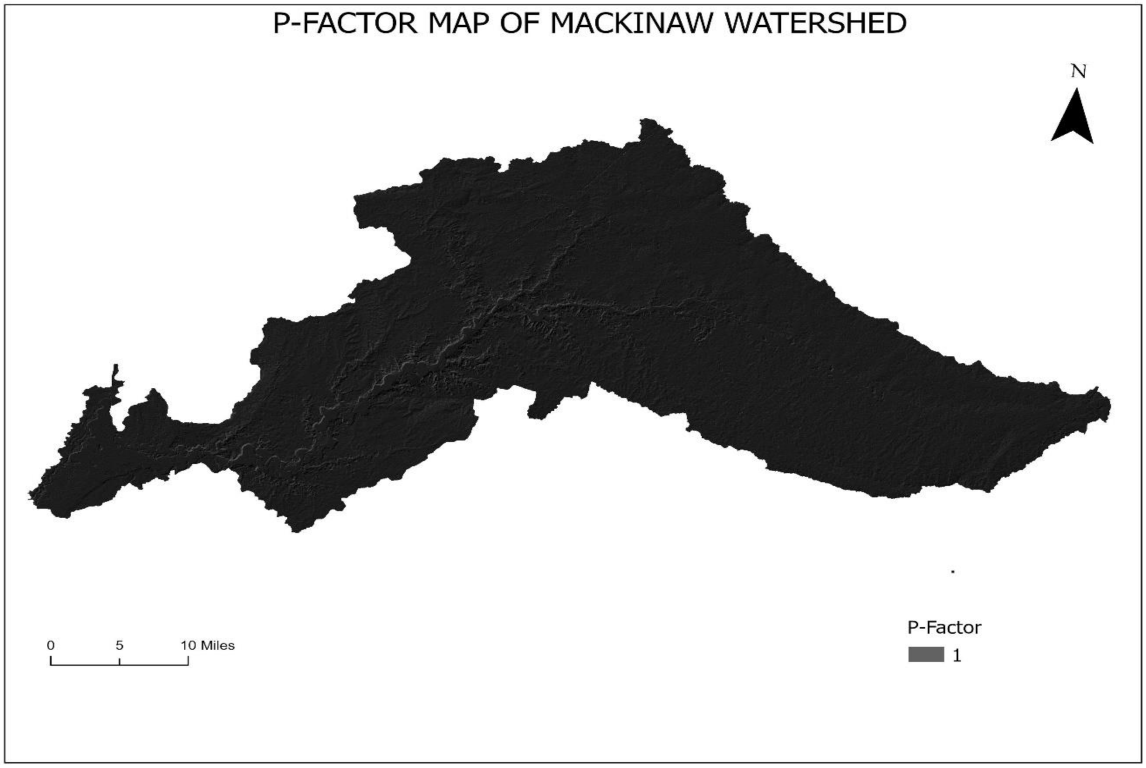

Fig. 3: P-Factor Map

Soil Loss Estimation: To identify each cell's soil loss in the Mackinaw watershed, a raster calculation was carried out using the RUSLE equation (A = R x K x LS x C x P).The raster layer output was further reclassified, using ranges defined by Parveenand Kumar (2012) as shown in figure 8 below. An deep knowledge of possible soil erosion throughout the research area as well as the soil loss map were supplied by the RUSLE model's output (Figure 7 and 8 and Table 1).

Table 1: Soil loss zone in watershed

Sl. No.	Soil Loss Zone	Range (in ton/ha/yr)
1	Slight	0 - 5
2	Moderate	5 - 10
3	High	10 - 20
4	Very High	20 - 40
5	Severe	40 - 80
6	Very Severe	>80

Soils with high K-factor values tend to be more susceptible to erodibility while the low K-factor values (Fig.2) are more resistant to erodibility. Sand and gravel are more resistant to soil loss compared to silt. Figure 3highi the raster made for the K factor. Majority of the high K (Figs. 2 and 3) values are in the Central to Western area of the map and also along the stream path within the study area. The analysis yielded several key findings regarding soil erosion prediction in the Mackinaw watershed. The LS-factor map in figure 4 confirms that the Mackinaw watershed's gently undulating terrain, which is typical of the Illinois landscape, explains why a sizable portion of the watershed exhibits minor to moderate potential soil loss. According to the raster output, the middle portion of the watershed, along the stream channel, where the steepest slopes and least stable soils were most common, will see the most soil loss. Areas that are most susceptible to erosion were identified by the spatial distribution of soil loss, which might help guide focused management tactics.

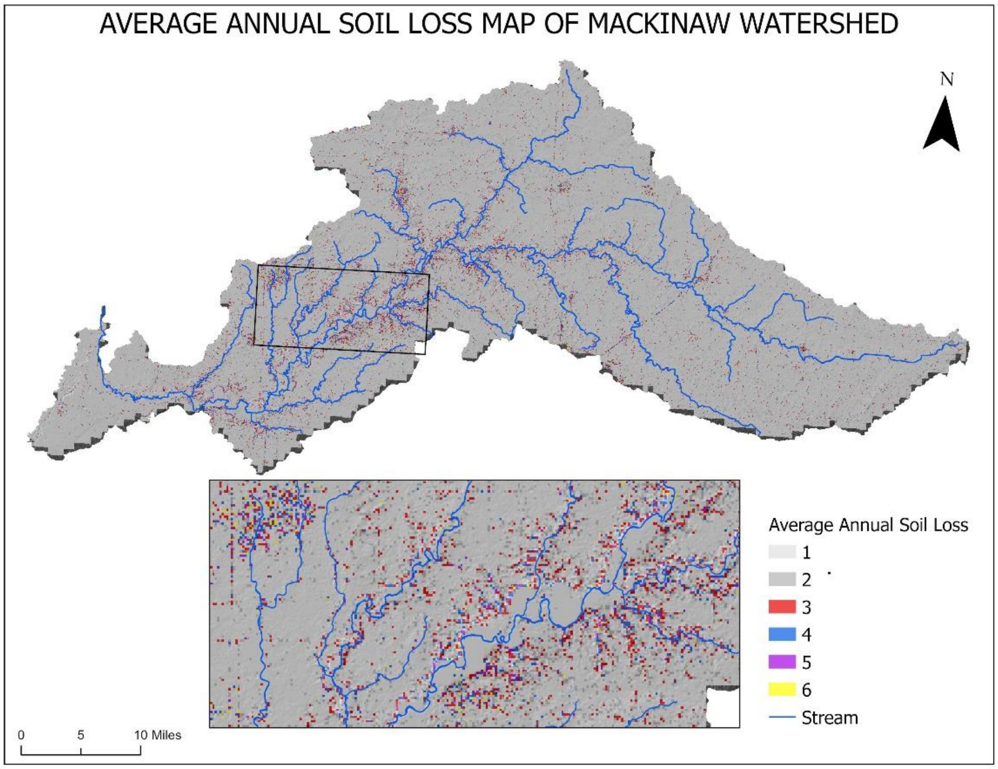

Fig. 8: Average annual soil loss map

4.0 Conclusion

This study shows how well the RUSLE framework and GIS can also be utilized to measure soil erosion. The combination of these technologies reveals regions that need erosion management attention and provides crucial information on the possible spatial spread of soil loss. The results highlight the necessity of focused management approaches to mitigate erosion risks and enhance the water quality.

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Consent for publication

Not applicable

Availability of data

Data shall be made available on demand.

Competing interests

The authors declared no conflict of interest

Ethical Consideration

Not applicable

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Authors' Contributions

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