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Evaluation of WEPP and Its Comparison with USLE and MUSLE in Yozgat-Kadılı Village

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ABSTRACT

The water erosion is a significant environmental issue in arid and semi-arid regions. It leads to soil degradation, reduced agricultural productivity, and desertification. This article used The WEPP, the USLE, and the MUSLE models to estimate the average soil loss in the Yozgat-Kadılı village. Also, The MUSLE model utilized the WEPP model-estimated runoff for soil loss estimation. The USLE model, which estimates soil erosion using six factors (R, K, L, S, P, and C), can be improved by incorporating the Modified Fournier Index (MFI). Results indicated that the MUSLE model (3.66 t/ha) performed well in estimating soil losses close to the observed value (3.15) in the wheat fields between 1986-1996. the MUSLE (5.31 t/ha) and WEPP (5.88 t/ha) models underestimated soil losses to the observed value (8.75 t/ha) in the fallow field for 1986-1996. The WEPP model estimated the highest average soil loss at 5.18 t/ha in a wheat field, while the USLE model yielded the lowest estimate at 1.28 t/ha between 1969 and 2020. The MUSLE model estimated the highest (4.94 t/ha) and The USLE model estimated the lowest (2.53 t/ha) soil loss in the fallow field between 1969-2020. Results also revealed that the WEPP model is needed to calibrate for estimating soil loss in arid and semi-arid regions.

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Introduction

Soil serves as the foundation for cultivating plants that provide us with food and fiber, and its quality significantly impacts crop production (Luetzenburg et al. 2020; Li et al. 2020). This quality depends on the interplay of physical, chemical, and biological properties. Unfortunately, soil erosion a naturally occurring phenomenon, alters these properties and ultimately reduces crop yield. Soil erosion is influenced by various factors, including land management practices, vegetation cover, and climatic conditions. These factors can lead to substantial variations in the soil's physico-chemical properties, impacting its ability to support healthy crop growth (Panagos et al. 2014; García-Ruiz et al. 2017; Babalık et al. 2021; Dursun and Babalık 2023; Demir and Dursun, 2024).

Soil erosion has become the most serious environmental problems today (Blanco and Lal., 2008). Unsustainable soil management practices and improper land use have led to the loss of large quantities of topsoil in a short period of time. The global annual soil displacement due to erosion is estimated to be around 24 billion tons (ÇMTUEP, 2005). In Turkey, the estimated annual soil displacement due to erosion is about 285.5 million tons (Berberoglu et al., 2020), Accelerated soil erosion is one of the most significant factors contributing to desertification and land degradation. This issue threatens the sustainability of agricultural production, natural resources, and ecosystems (Özşahin, 2024). Given the extensive economic and environmental impacts of soil erosion, it is evident that urgent protective measures and conservation efforts are required. Without these measures, the continued degradation of soil resources will persist, compromising the effective utilization of natural resources (Erkal and Yıldırım., 2012). Accurate measurement and estimation of soil erosion is a complex and costly process. On-site measurements are time-consuming and limited to specific areas. Therefore, the development and application of erosion models have become increasingly important. These models simulate and predict soil loss by considering various factors, allowing for the estimation of erosion over larger areas and the reduction of associated costs (Djoukbala et al.,2019). Moreover, they provide essential information for the sustainable management of soil and water resources. The accuracy of model predictions is evaluated by comparing them with field observations and measurements. Calibration and validation of these models must be conducted in a manner appropriate for regional conditions. This approach enables the implementation of effective soil conservation measures and informed land use planning (Kinnell, 2020).

Soil erosion models are mathematical tools that simulate the erosion process. These models play a vital role in various applications, including dam design, environmental planning, and natural resource protection. While empirical models are valuable for estimating sediment yield, process-based models offer greater applicability across diverse spatial and temporal contexts. This is particularly true for understanding the long-term impacts of erosion. The Universal Soil Loss Equation (USLE) developed by Wischmeier and Smith in 1965 is the most widely used model for estimating soil erosion by rainfall and runoff. This equation considers several factors, including rainfall patterns, soil properties, topography, and land management practices, to calculate the average annual soil loss.

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

Where: A is the estimated soil loss per unit area, R is the rainfall erosivity factor, representing the erosive power of rainfall, K is the soil erodibility factor, indicating the susceptibility of the soil to erosion, LS is the slope length and steepness factor, considering the slope characteristics, C is the cover and management factor, accounting for land cover and management practices, P is the support practice factor, representing the effectiveness of conservation practices. Researchers and conservationists use this equation to assess soil erosion risk, develop soil conservation strategies, and understand the impact of different factors on soil loss. It's important to note that variations and adaptations of the USLE exist to suit specific geographic regions and conditions.

The rainfall erosivity factor (R) captures the combined impact of raindrop impact and subsequent runoff generation. The topographic attributes of the terrain are represented by the slope length factor (L) and slope steepness factor (S), which influence the rate of energy dissipation and erosion potential. The cover and management factor (C) specifically addresses the magnitude of soil loss occurring on agricultural lands during fallow periods under prevailing environmental conditions.

The USLE model has been a commonly used tool for soil erosion prediction and management worldwide (). Researchers often validate the model predictions by comparing them with observed data from field measurements or erosion plots. Calibration and validation exercises help refine the model parameters and improve its accuracy for specific regions or land uses.

The USLE model has been a commonly used tool for soil erosion prediction and management worldwide (Wischmeier and Smith, 1965; Ghosh et al., 2013; Bagarello et. al., 2014; Di Stefano et. al., 2017; Kinnell, 2020). Researchers often validate the model predictions by comparing them with observed data from field measurements or erosion plots. Calibration and validation exercises help refine the model parameters and improve its accuracy for specific regions or land uses (Flanagan et al., 2018).

The Modified Universal Soil Loss Equation (MUSLE) model is an erosion model developed by Williams, (1975). It includes factors such as rainfall, soil properties, land use, and topography from the USLE model's algorithm to estimate sediment yield based on individual rainfall events (Ran et al., 2019).

Williams, (1975), simplified the estimation of stream sediment yield for individual storm events by substituting the rainfall factor (R) with a runoff factor in the USLE. MUSLE was developed by collecting data from 778 storm-runoff events from 18 small watersheds, with areas ranging from 15 to 1500 hectares, slopes from 0.9 to 5.9%, and slope lengths of 78.64 to 173.74 m. The MUSLE is given in the following revised form:

$$S = 11.8(Q\, q_p)^{0.56} \quad (\text{K LS C P}) \quad (2)$$

Where S is the sediment yield (t), Q is the intensity of the runoff (m^3), q_p, is the surface flow peak value ($m^3\ s^{-1}$) and K, L, S, C, and P factor values were used as given in the USLE equation. K, L, S, C, and P are soil erosion sensitivity (t ha h ha^{-1} MJ^{-1} mm^{-1}), slope length, slope steepness, agricultural management, and soil erosion control application factors, respectively, and similar to the USLE model. As a and b are position coefficients. For the areas where the equation was developed, a and b were determined to be 11.8 and 0.56 for metric system units, respectively.

The MUSLE has been applied in many different basins and for different purposes around the world

(Lopez-Tarazn et al. 2012; Khaledi Darvishan et al., 2009; Zhang et al., 2009; Sadeghi et al., 2008, 2007a, 2007b; Varvani et al., 2006; Kandrika and Venkataratnam, 2005; Sadeghi 2004; Sarkhosh et al., 2004; Cambazoglu and Gogos, 2004; Fontes et al., 2004; Kandrika and Dwivedi, 2003; Erskine et al., 2002; Khajehie et al., 2002; Rezaiifard et al., 2002; Kinnell and Riss, 1998; Banasik &Walling, 1996; Nicks et al., 1994; Das, 1982; Asokan, 1981), and this model has been modified in some cases. Since the MUSLE model was produced for specific conditions, its application without calibration caused huge errors.

The USDA developed the Water Erosion Prediction Project (WEPP) in 1985 to model soil erosion caused by water. The model takes into account various factors such as climate, topography, soil properties, and land management practices. Compared to previous models like the USLE and its revised version the Revised Universal Soil Loss Equation (RUSLE), the WEPP model presents a more detailed and process-based approach to erosion prediction. It comprehensively considers factors such as infiltration, runoff, and sediment transport.

The WEPP model is widely used because it provides more detailed and location-specific predictions than previous models like the USLE and the RUSLE. Researchers and land managers use the WEPP model to evaluate the potential effects of various scenarios, including degradation in land use and erosion control practices on soil erosion (Elliot and Flanagan, 2023 Revuelta-Acosta et al., 2021; Zheng et al., 2020). The WEPP model requires weather and climate data as inputs for predicting soil erosion caused by water. The model uses climate files that contain historical or synthesized meteorological data to simulate the effects of weather on soil erosion processes. The WEPP model employs the Green-Ampt equation to estimate the rate of rainfall infiltration into the soil. This equation takes into account the soil's hydraulic properties and initial moisture levels, making it a useful tool for simulating water movement through unsaturated soil. Understanding this process is essential for predicting runoff and sediment transport, which are critical factors in soil erosion modeling. The steady-state continuity equation of the WEPP model is one of the fundamental equations used in soil erosion models, particularly for simulating the movement of water and erosion:

$$\mathrm{dG}/\mathrm{d_x} = \mathrm{D_f} + \mathrm{D_i} \quad (3)$$

Where; *dx*: Total erosion amount at a specific area or point, *Df*: Amount of interrill erosion (surface erosion), *Di*: Amount of rill erosion. Equations are used in modeling soil erosion by separating it into different processes (e.g., surface erosion and rill erosion). Interrill erosion generally represents erosion caused by direct rainfall on the soil surface and surface flows while rill erosion represents erosion originating from deepening channels.

Another difference between WEPP and other models is that the continuous sediment equation is applied in rills from uniform flow hydrology suggests that the WEPP model incorporates a continuous sediment equation specifically designed for rill erosion within the framework of uniform flow hydrology.

Sediment may form in the interrill area then be transported downslope or accumulate in rills. The rill detachment capacity in the WEPP is calculated when the surface hydraulic shear stress exceeds the critical shear stress of the soil with the equation 4 given below:

$$\mathrm{D_c} = \mathrm{K_r}(\tau_\mathrm{f} - \tau_\mathrm{c}) \quad (4)$$

Where Dc is the detachment capacity of the rill flow, Kr is the rill erodibility of the soil, τf is flow shear stress acting on soil particles, and τc is the rill detachment threshold parameter or critical shear stress of the soil.

Rill detachment is zero if the shear stress of the runoff is less than the shear stress of the soil. In modeling or simulation, if the shear stress from runoff water is below a critical threshold for the soil, rill detachment the process of soil particle detachment leading to rill formation does not occur and equation 5 is calculated:

$$\mathrm{D_f} = \mathrm{D_c}\left(1 - \frac{\mathrm{G}}{\mathrm{T_c}}\right) \quad (5)$$

Where D_f is the net rill detachment, and Tc is the transport capacity of flow in the rill. In erosion models, four hydraulic processes play a crucial role: peak surface runoff, effective surface runoff duration, effective rainfall intensity, and effective rainfall duration (Spadaro et al., 2018). Peak surface runoff measures the highest flow rate of water in a given area, indicating how quickly precipitation-induced water converges on the soil surface (Dutta et al., 2016). Effective surface runoff duration shows the period during which surface runoff is in effect reflecting the duration of precipitation-induced water flow on the soil surface. Effective rainfall intensity quantifies the amount of rainfall per unit area over a defined period indicating the density of impactful precipitation in a particular region. Effective rainfall duration represents the duration for which precipitation affects a specific area. These hydraulic factors are crucial in assessing and simulating soil erosion, taking into account precipitation dynamics, soil characteristics, and topographic features (Flanagan et al., 2018).

The validation process of the WEPP model involves assessing its performance against observed data, aiming to gauge its accuracy (Elliot et al., 1995). This assessment entails comparing field data or other sources to evaluate the model's performance, serving as a basis for identifying areas of improvement and estimating errors. Enhancements may involve adjusting model algorithms, refining parameters, or improving input data quality. Additionally, optimizing parameters specific to the region or usage scenario is often necessary during the validation process. Scientific literature systematically records these enhancements and parameter adjustments, furnishing a robust framework for enhancing the performance of the WEPP model. Numerous studies have conducted sensitivity analyses of the WEPP model, which involve evaluating how variations in parameters affect model outputs. These analyses are critical for understanding the model's behavior, enhancing its reliability, and gaining insights into its performance under specific conditions (Wang et al., 2023; Erdoğan Yüksel et al.,2019; Demir et al., 2018; Nearing et al.,1990). Typically, researchers manipulate individual parameter values and observe their impacts on model outputs. Precipitation, soil properties, vegetation cover, slope, and erosion control practices are some of the parameters that influence the WEPP model's performance. In other studies, researchers have focused on examining precipitation patterns. These analyses aim to investigate the sensitivity of the WEPP model to precipitation variables and its response to different precipitation scenarios. Researchers typically manipulate precipitation quantities, distributions, or intensities to assess the resultant changes in the model outputs. Precipitation is a critical input parameter for the WEPP model. It has a significant impact on erosion and surface runoff. Therefore, sensitivity analyses that focus on precipitation variables are crucial for understanding how the model responds to different precipitation conditions and for improving its performance conditions (Wang et al., 2023; Erdoğan Yüksel et al.,2019; Demir et al., 2018; Nearing et al.,1990. For example, changes in precipitation distribution can be explored to enhance the model's outputs under specific rainfall regimes. These studies provide detailed insights into the WEPP model's reactions to precipitation variables. They contribute to more effective erosion control and soil management strategies, especially in arid and semi-arid areas where precipitation is a significant factor.

Soil erosion is a critical issue for sustainable agriculture and environmental management on a global scale, and empirical and physically-based models such as USLE, MUSLE, and WEPP are widely employed for its assessment. The comparability and applicability of these models are facilitated by their use of various methods and parameters. Specifically, USLE is an empirical model, MUSLE is semi-empirical, and WEPP is a physically-based model. This diversity allows for a more comprehensive evaluation of each model's strengths and weaknesses. USLE and MUSLE operate at the field scale, whereas WEPP operates at the watershed scale. Comparing models at different scales contributes to understanding the impact of scale on model selection. there has been no study comparing the performance of USLE, MUSLE, and WEPP models in predicting soil loss specifically in the Central Anatolia region. Most existing studies in this region have utilized only a single model, highlighting the importance of evaluating the effectiveness of these three models together under Central Anatolian conditions. The region's semi-arid climate, high soil erodibility, and intensive agricultural activities make it a unique context for this evaluation. Assessing the sensitivity and prediction performance of USLE, MUSLE, and WEPP models to the specific conditions of Central Anatolia is crucial for identifying the most appropriate model for the region. Additionally, comparing the results of field-scale and watershed-scale models will provide insights into the impact of scale on prediction accuracy. This evaluation may also guide the development of a scale-compatible model for Central Anatolia in future research. In summary, a comprehensive assessment of the USLE, MUSLE, and WEPP models, when applied together in the Central Anatolian region, will provide valuable insights for both academic and practical applications. The study aims to compare soil loss predictions from these models with observed data from 1986-1996 and to test their performance over the extended period from 1969-2020. This approach will ensure a thorough evaluation of each model's accuracy and applicability, offering significant contributions to the sustainable management of soil and water resources in the region.

Materials and Methods

Study Area

The study was conducted in Kadılıl village located 10 km from the Sarıkaya county by the Yozgat-Kayseri highway in Turkey (Figure 1). The study location is situated between 39° 32'13'' N latitudes and 35°18'14''E longitudes. The semi-arid continental climate of the Central Anatolia region dominates Yozgat province. Owing to its isolation from the sea, summers are hot and dry, while winters are cold and rainy. There are significant temperature differences between summer and winter and day and night. The coldest months are January and February, while July and August are the hottest months (Yozgat Çevre ve Şehirçilik İl Müdürlüğü, 2020). Yozgat, located at an altitude of 1300 m, experiences significant temperature and precipitation differences from the surrounding area. Precipitation has an irregular distribution throughout the year, and winter and spring are the rainy seasons in Yozgat. Precipitation is generally in the form of snow and starts in early November and continues until the first week of May. The average annual temperature in the region is 9.08°C, and the average annual precipitation is 418.7 mm. Due to its geographical location, the prevailing wind direction in Yozgat is northeast. The average wind speed is 2.03 m/s, while the fastest wind recorded is 19.1 m/s (Meteoblue, 2023).

Figure 1. Location map of the study area

Model Definitions, Data Entry, and Output Evaluation

The data required for these equations were obtained through experiments and observations conducted over a period of 10 years. During this process, various meteorological data, land measurements, soil analyses, and vegetation assessments were carried out. Long-term data collection allowed for a more accurate determination of the impacts of climate changes and land use on erosion. These data were used for the calibration and validation of the models, enabling erosion predictions that are appropriate for regional conditions. The R factor in the USLE was determined through the use of the Fournier index, which is also referred to as the "precipitation erosivity index". This index takes into account the relationship between transported material, climate data, and topographic features (Lal, 1988). Considering the erosional power and precipitation characteristics of soils, the MFI is used as a guide for taking soil and water protection measures in areas with erosion risk. In the study, there is observed soil loss for the years 1986-1996. Monthly total precipitation for these years was determined and the monthly MFI was calculated for each year using Eq.6:

$$\mathrm{MFI} = \sum_{1}^{12} \frac{\mathrm{p^2 i}}{\mathrm{p}} \tag{6}$$

Where, Pi is total precipitation in (i) month, mm, and P is annual average precipitation, mm.

The relationship between the annual observed and predicted MFI between 1987 and 1996 was determined (Figure 2). R values were calculated by substituting the values obtained from this relationship in Eq.7:

$$\mathrm{R} = (1.1909 \times \mathrm{F}) - 4.2297 \quad \mathrm{n} \tag{7}$$

The K factor was determined based on laboratory analysis of each soil sample utilizing Eq.8:

$$100\times K=((2.1\times10\text{-}4)(M1.14)(12\text{-}a)+(3.25\times(b\text{-}2)+2.5\times(c\text{-}3) \tag{8}$$

Where K is soil erosion factor, M is particle size matter, a is organic matter content, %b is structure type code, and c is water permeability code. The particle size (M) in the equation is determined by Eq.9:

$$M = (\text{very fine sand + Silt}) \times (100 - \text{Clay}) \tag{9}$$

The average K value for 1987-1996 was calculated to be 0.15 and used for other years. The P factor, representing the soil conservation factor value, was calculated for observed years, while a value of 1.00 was used for the other years. For the C factor, 0.18 and 0.3653 values were used for wheat and fallow lands, respectively. The LS value is taken as 1 because the study area has a slope of 9° and a length of 22.1 meters.for the entire study period.

The MUSLE Model. Runoff volume (Q) and peak runoff rate (qp) were calculated with the WEPP model since there is no observation station in the basin.

The WEPP Hillslope version model (Flanagan and Nearing, 1995) was utilized in this study. To effectively use the model, it was crucial to prepare four separate input files for each study area. These files contained detailed information on the climate, topography, soil characteristics, and land use of the research area. The raw data from the records at the Tokat Gaziosmanpaşa University Agricultural Laboratory were translated into WEPP input file format over many years. The WEPP model utilizes two distinct types of climate files. One is the breakpoint format data, and the other is the daily'ip-tp' format data (intensity-at-peak factor and time-to-peak factor) as described by McGehee et al. in 2020. Because of the unavailability of breakpoint data for all precipitation events, we chose the 'daily ip-tp format' for our analysis. Moreover, the WEPP modeling system incorporates a stochastic climate generator (CLIGEN) developed by Nicks et al. (1995). CLIGEN generates daily estimates for various climate parameters such as precipitation, time to peak, peak intensity, storm duration, maximum and minimum temperature, dew point temperature, wind speed and direction, and solar radiation for a specific geographical point, as highlighted by Srivastava et al. (2019). In this study, two different CLIGEN input files were used for a WEPP model: they covered the period 1986–1996, and 1969-2022, respectively. Studies evaluating the performance of the CLIGEN climate model in Turkey are quite limited. Demir and Oğuz (2019) evaluated the performance of the CLIGEN climate model in simulating seasonal precipitation data in Tokat Province, Turkey. The study found that the CLIGEN model successfully predicted the precipitation during Tokat's dry season. Specifically, the model demonstrated accurate predictions for winter and spring precipitation, with observed and predicted values being closely aligned. However, it was noted that the model's performance was less effective during the summer season. Demir et al. (2018) conducted a study where daily precipitation data from the Tokat meteorological station between 2005 and 2015 were simulated using the CLIGEN precipitation model and compared with the observed data. The results demonstrated that while CLIGEN exhibited limited accuracy in estimating daily precipitation data, it showed improved performance in predicting monthly and annual precipitation totals. Specifically, the model tended to underestimate observed daily precipitation, particularly during the spring and winter months, yet it performed well in simulating the annual total average and monthly average precipitation. Overall, this study provided a comprehensive evaluation of the CLIGEN model's performance under the climatic conditions of Tokat Province, highlighting both its capabilities and limitations.

The slope input files were built using the erosion plot slope length, width, and shape based on the topographic information. All the plots had a uniform slope and width used in the USLE. Soil input files were generated based on measured data. The soil parameters were not calibrated.

The texture data, the organic matter, cation exchange capacity and the percent rock content were available in the measured data set on all plots (Table 1).

Table 1. The study used soil data

Analyzes	Depth (cm) 0-20
OM %	4.5
Sand %	34.3
Clay %	28.7
Silt %	37
VFS %	16.4
CEC Meq/100	7.7
Rock	2.7

Table 2. The study used erodibilite data

Erodibilite Parameters	Results
İnterill (kg×s/m×4)	5.86884e+006
Rill (s/m)	0.0069
Critical Shear (N/m×2)	3.6
Eff. Hid. Con. (mm/hr)	7.38

Other soil parameters were calculated such as baseline interrill erodibility (k_i), baseline rill erodibility (k_r), baseline critical shear stress (c), and baseline effective hydraulic conductivity (k_e) based on the equation developed in Risse et al., (1994) and given in the WEPP user's manual (Flanagan and Livingston, 1995).

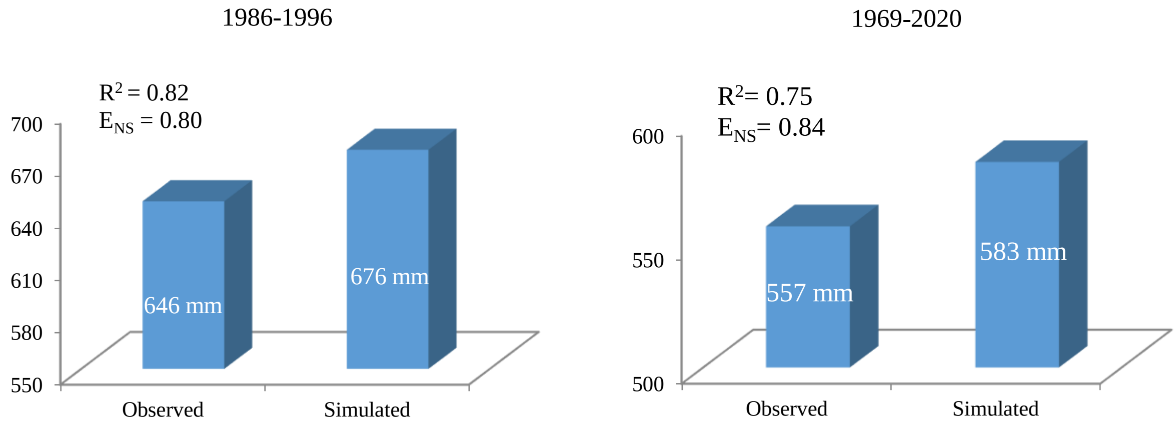
Management input file included detailed information on plant physical growth, residue properties and decomposition, tillage operations, residue management, and all relevant dates, management practices and initial conditions, etc. The information was incorporated in the management file based on the recorded data available and the WEPP crop input information. This study evaluated the 10-year individual soil loss data of two different parcels, wheat and fallow. Wheat was sown manually in October with inclinations opened toward the slope. Both October and spring fertilization was performed, and wheat was harvested in July. Fallow was left unplanted for a year (Table 3). Concerning crop growth parameters, the biomass energy ratio, harvest index, and optimum yield under non-stress conditions were adjusted to match the observed plot crop yield. All other crop growth parameters are assumed to be the same as those specified in the WEPP default database (Flanagan and Livingston, 1995).

Model Evaluation

The model performance was assessed using the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE) (Eq. 11). The N_{SE} indicates the agreement between the observed and predicted values (fit to the 1:1 line). Perfect agreement is reached with an N_{SE} value of 1. Brooks et al. (2016) indicated that when using the daily output for streamflow prediction from an uncalibrated model, an N_{SE} above 0.30 is a good indication that the fundamental mechanics of the model are correct.

Table 3. The study used management file

Tillage System	Cropping System	Tillage operation and dates
Wheat	Annual continuous winter wheat (harvest on 15 July, planting 15 Oct.	Tillage: Disk plow, 1 Oct. Tillage: Field cultivator, secondary tillage, 1 Oct. Tillage: Plow molboard, 8”, 1 Aug. Plant: Winter wheat, 15 Aug. Harvest: 15 July
Fallow Tilled	Annual continuous	Tillage: 15 May, June, July, Aug, Sep.



(a) (b)

Figure 2. The relationship between observed and simulated rainfall, a. 1996, b.2020

Foglia et al. (2009) considered N_{SE} values below 0.2 insufficient, 0.2–0.4 sufficient, 0.4–0.6 good, 0.6–0.8 very good, and greater than 0.8 excellent. R^2 represents the proportion of observed data that can be explained by the model. (Foglia et al., 2009; Moriasi et al., 2007).

$$E_{NS} = \frac{\sum_{n}^{n} 1(Q_1 - Q^1)^2}{\sum_{n}^{n} 1(Q_1 - Q)^2} \quad (11)$$

Results and Discussion

The CLIGEN 5.3 model was used to determine daily precipitation, maximum and minimum temperature, solar radiation, wind intensity, and direction at Yozgat weather stations from 1986 to 1996 and from 1969 to 2020. The observed annual precipitation from 1986 to 1996 and from 1969 to 2020 was 646 and 557 mm, respectively. The annual precipitation at the CLIGEN model was similar to observed annual precipitation for both 1986 to 1996 and 1969 to 2020 periods. The simulated annual precipitation was 676 mm for 1986-1996, and 583 mm for 1969-2020 (Figure 2).

The monthly change in winter precipitation (October-March) was uniform for both periods and the observed annual precipitation the simulated annual precipitation for 1986-1996 was slightly higher than that for 1969-2020. However, the change of precipitation in summer (April-September) monthly was not uniform, while in July and August, the mean precipitation for 1969-2020 was much higher than that for 1986-1996.

Soil Loss Results in the Wheat Field for the Period 1986-1996

Soil loss estimates were calculated for each type of land use in the Yozgat-Kadılı region for comparison of the USLE, MUSLE, and WEPP on average annual soil loss. Table 4 presents the statistics for the analysis based on average annual values of soil loss predicted by these models. The observed precipitation data were used to calculate the Fournier precipitation index for average annual soil loss values predicted by the USLE model. The average index, calculated separately for each year, was found to be 45.36 mm per year from 1986 to 1996. The average index was 45.36 mm per year from 1986 to 1996. The average annual soil loss predicted by the USLE model for wheat land was 1.97 t/ha, with a range of 0.11 to 11.08 t/ha. MUSLE and WEPP models predicted average annual soil losses of 3.67 and 3.42 t/ha, respectively.

The average annual soil loss values by MUSLE and WEPP were found to be close to average measured soil loss values. Figure 3a shows a comparison between the USLE soil loss estimate and the observed average annual soil loss in a wheat field. The USLE model was underestimated soil loss values more than observed soil loss values. The model correlation coefficient (R^2) for the WEPP models was less than 0.70; indicating poor performance in predicting average annual soil loss. On the other hand, the USLE and MUSLE models showed higher R^2 values for the average annual values (0.78 and 0.83 respectively) than the WEPP model. These findings are consistent with a previous study on the application of the USLE model in the Konya Plain, Turkey (LaRocque et.al., 2013).

Table 4. Observed and Simulated Soil Loss Results: Using WEPP, MUSLE, and USLE in the wheat field

Land use	Mean Soil Loss (t/ha)			
	Observed	USLE	MUSLE	WEPP
Wheat	3.90	1.97	3.67	3.42

Table 5. Observed and Simulated Soil Loss Results: Using WEPP, MUSLE, and USLE in the fallow field

Land use	Mean Soil Loss (t/ha)			
	Observed	USLE	MUSLE	WEPP
Fallow	7.52	3.65	6.49	7.19

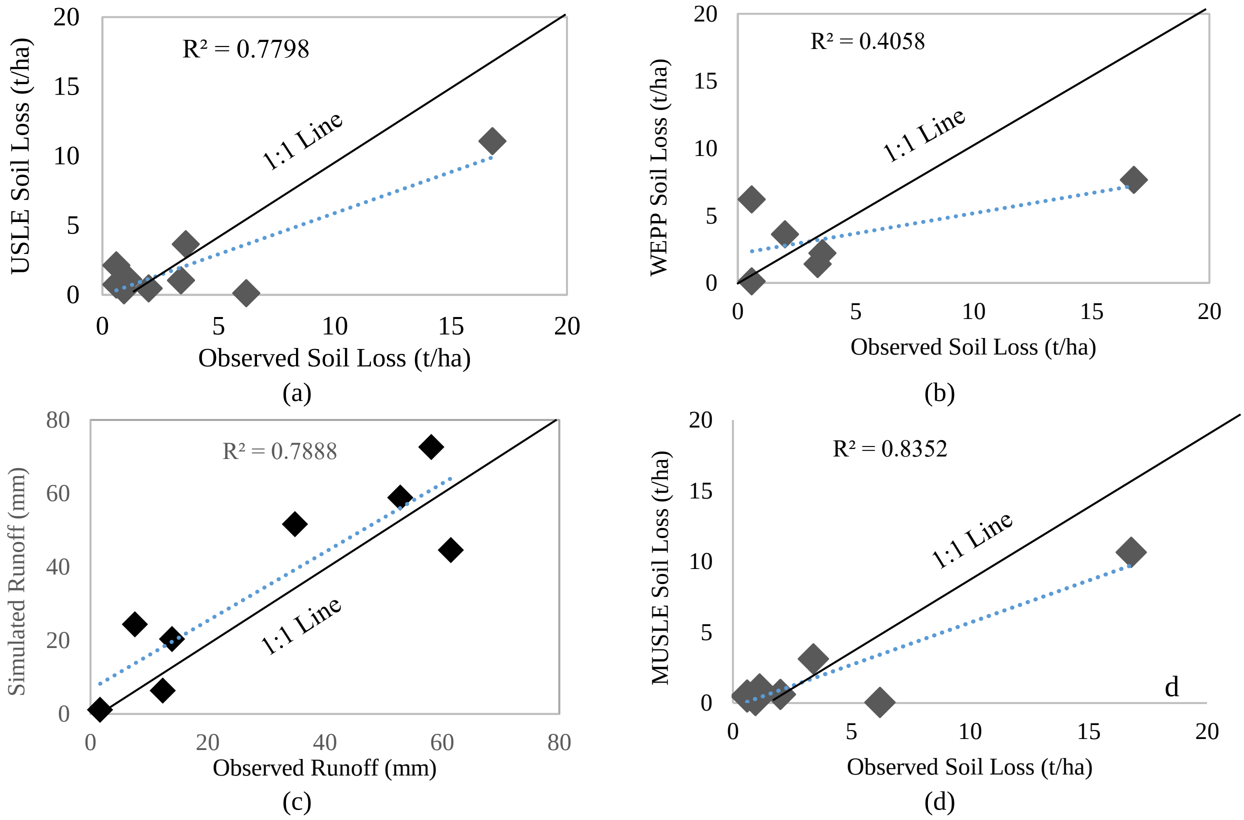


Figure 3 (a) Comparison of estimated average annual soil erosions by USLE, (b) The relationship between observed and uncalibrated surface runoff in wheat field, (c) Comparison of estimated average annual soil erosions by MUSLE, (d) Comparison of estimated average annual soil erosions by WEPP in wheat fields.

The WEPP overestimates low values and underestimates a majority of high values (Figure 3b). This phenomenon is common in all erosion models, but it appears to be more prevalent in WEPP compared to other models. The study area has an arid climate and the soils are quite resistant to these climatic conditions. Surface runoff and annual rainfall amounts are low in some years. Hence, the model may be limited in considering the effect of certain climatic factors such as drought.

The MUSLE model utilized the WEPP model to predict runoff data for both wheat and fallow fields. This model was integrated with other models to produce comprehensive results in the study of soil erosion mechanisms in different farming regions. This integration can play a significant role in devising effective strategies to tackle soil erosion issues. Using integrated data from these models can offer a more accurate evaluation of the sustainability of farming practices and the efficiency of soil management techniques. Before estimating soil losses using the MUSLE method, surface runoff data from 1986 to 1996 were estimated using the WEPP model (Figure 3c). The results showed a close relationship between the observed and predicted data. The WEPP model: $R^2 = 0.79$, $E_{NS} = 0.56$ with surface runoff. The results demonstrate the WEPP model's ability to accurately forecast runoff data, as evidenced by its close proximity to observed data. The considerable R^2 value obtained indicates the model's capacity to explain the runoff data. Moreover, the moderate E_{NS} value close agreement between the model predictions and the observed data. Figure 3d present plots of measured the MUSLE model estimated values of soil loss. Figure 4b, it becomes apparent that the MUSLE model tends to overestimate soil loss for smaller values. A previous study conducted in Malaysia by Mohammed (2021) compared soil losses using the USLE and MUSLE models in a study area divided into five distinct catchments. The study revealed that the MUSLE model performed better than the USLE model due to continuous rainfall in the study area, which caused soil loosening and surface runoff. These findings support our results as well.

Figure 3(a) Comparison of estimated average annual soil erosions by USLE, (b) The relationship between observed and uncalibrated surface runoff in wheat field, (c) Comparison of estimated average annual soil erosions by MUSLE, (d) Comparison of estimated average annual soil erosions by WEPP in wheat fields.

When comparing USLE, MUSLE with WEPP, the Nash and Sutcliffe model efficiency was highest close to each other for USLE and MUSLE (0.41 and 0.42 respectively), followed by 0.15 for the WEPP model. This shows that USLE and MUSLE performed slightly better than the WEPP model in predicting average annual soil erosion.

In the fallow field, the observed average annual soil erosion was 7.52 t/ha. The three models used to predict average annual soil loss were USLE, MUSLE, and WEPP, and they predicted 3.65 t/ha, 6.49 t/ha, and 7.19 t/ha, respectively (Table 5). The USLE model underestimated soil loss, as shown in Figure 4a. The USLE underestimated soil loss in 1991 and 1992 when actual losses were higher. This suggests limitations in the USLE model, particularly in situations where soil splash and movement tendencies are minimal (Alewell et al., 2019). These findings indicate that USLE performance may vary over time and under different conditions, potentially not fully capturing reality in certain scenarios. Therefore, we recommend using more accurate and spatially distributed data on the soil and climate characteristics of the study area and incorporating more process-based models for large-scale applications (Mohammed et al., 2021).

Figure 4b presents plots of observed and WEPP-predicted values of soil loss.

In Figure 4b it is apparent that WEPP overestimates soil loss for the small values. These values demonstrate the model's consistency with observed data, and indicate its ability to account for rainfall, surface runoff, and soil properties. The findings have confirmed that the model accurately simulates the processes of soil erosion. Han et al. (2016) reported that the model-predicted erosion was greater than the observed erosion. At the slope scale, under different coverages, the simulated erosion was slightly higher than the measured erosion. When the coverage is 40%, the simulated results of both runoff and erosion are the best.

The MUSLE method was used to estimate soil loss in the fallow land according to the procedure described for the wheat field. The only difference was that the management file was changed and runoff data was estimated. We compared the estimated and observed data and presented them in Figure 4c. The coefficient of determination (R^2) and the E_{NS} values were 0.84 and 0.54, respectively. The observed runoff values were low in the fallow land, and the study area had an arid climate. WEPP overestimates low values and underestimates high values. The WEPP model could not predict the high rainfall values for each year. Therefore, MUSLE underestimated soil loss in some years. The results obtained in this study were consistent with those of previous studies. Alewell et al. (2019) reported that the MUSLE model performed well in estimating soil loss in Mediterranean catchments. Still, it was sensitive to input parameters such as soil texture, slope, and land management practices. Another study reported that the WEPP model could reasonably predict runoff in agricultural lands and forest ecosystems, but it overestimated runoff in burned forest ecosystems. They also reported that the WEPP model was limited in accounting for certain climatic factors such as drought (Al-Ani & Ola,2019).

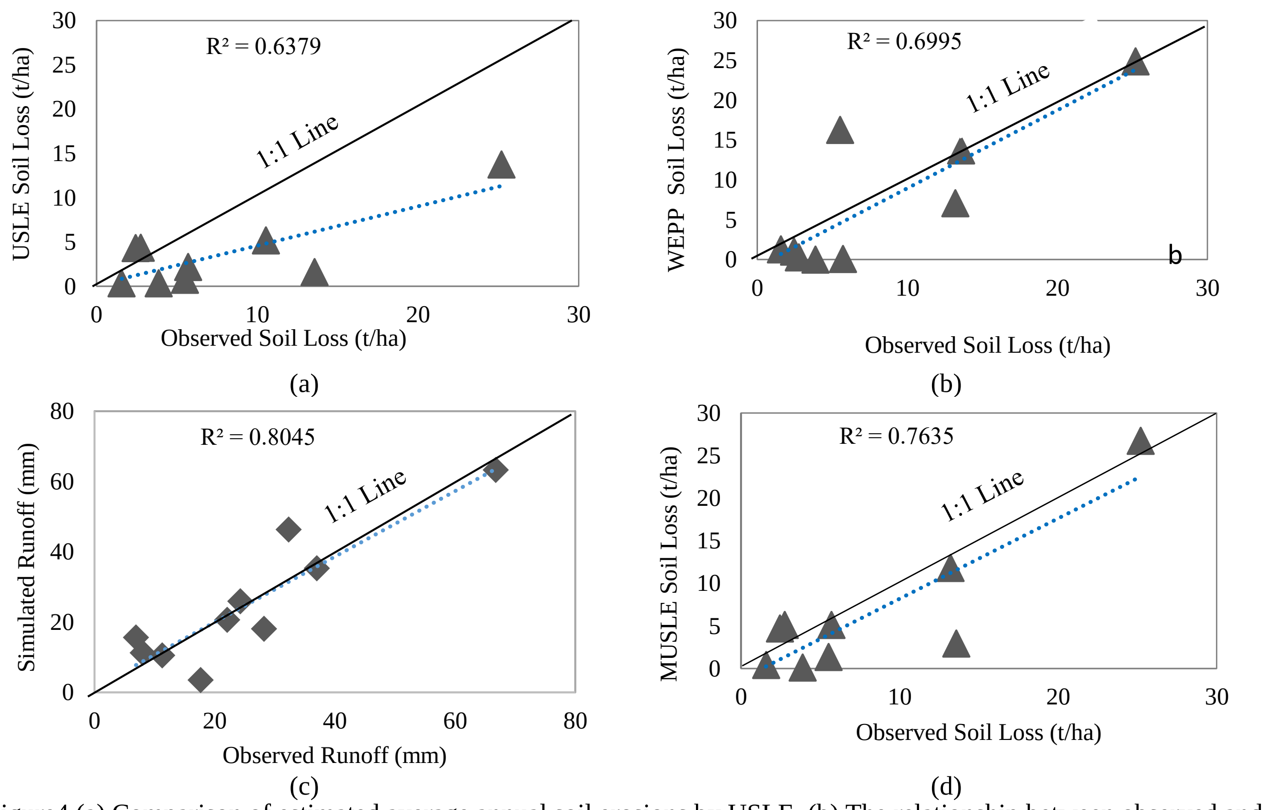


Figure4 (a) Comparison of estimated average annual soil erosions by USLE, (b) The relationship between observed and uncalibrated surface runoff in fallow field, (c) Comparison of estimated average annual soil erosions by MUSLE, (d) Comparison of estimated average annual soil erosions by WEPP in fallow fields.

Table 6. Simulated Average Soil Loss Results for 1969-2020 using WEPP, MUSLE, and USLE in the wheat field.

Parameter	USLE	MUSLE	WEPP
Average	2.60	4.58	3.15
SD	1.65	4.57	1.81
Skew	2.57	2.19	0.69

Table 7. Simulated Average Soil Loss Results for 1969-2020 using WEPP, MUSLE, and USLE in the fallow field.

Parameter	USLE	MUSLE	WEPP
Average	1.28	3.45	6.14
SD	0.84	2.54	5.4
Skew	2.99	1.88	1.68

On the other hand, the average annual soil loss values predicted by MUSLE (6.49 t/ha) were very close to the observed annual average soil values (7.52 t/ha), as illustrated in Figure 4d.

When comparing USLE, MUSLE with WEPP correlation coefficient values, the results show that the MUSLE correlation coefficient value was highest (0.76), followed 0.70 by WEPP for WEPP and 0.64 for USLE. According to the Nash and Sutcliffe model efficiency, MUSLE had the highest efficiency of 0.44, followed by WEPP with 0.37, and USLE with 0.22. The lower values of R^2 and E_{NS} for USLE indicate that the model was strongly affected by environmental conditions and had limited agreement with the observed data.

Soil Loss Results in the Wheat Field for the Period 1969-2020.

The estimated average annual soil loss in a wheat field between 1969 and 2020 by the USLE, MUSLE, and WEPP models were 2.60 t/ha, 4.58 t/ha, and 3.15 t/ha, respectively (Table 6). The highest soil losses predicted by The USLE for both wheat and fallow land occurred in 1996. The reason for the high soil losses is the high intensity of precipitation. Rainfall in March, April, and August impacted soil loss. In particular, short-term but very heavy rains occurred in April. Jemai et al. (2021) assessed soil erosion by the USLE in a Tunisian region. They stated that the insufficient dataset for validation was due to the region's heterogeneous structure and arid climate. These findings support the results obtained in our study.

In this study, soil loss estimates were compared using different erosion models (WEPP, USLE, MUSLE) between 1969 to 2020 (Table 6). The results present significant findings in the context of model selection and soil erosion assessments. The USLE and WEPP models yielded similar results in soil loss predictions. This demonstrates the effectiveness of both models in representing general erosion processes and their applicability to different soil types and terrains. The MUSLE model tended to predict higher soil loss predictions compared to the USLE model cannot be attributed to a single factor alone. Multiple factors contribute to this phenomenon. These factors include topographic variables such as slope length and steepness, the significance assigned to surface runoff, model parameters, as well as land factors like soil cover type and land use. The study area has arid climatic conditions, and the MUSLE model is closely related to surface runoff. Djoukbala et al. (2019) conducted a study to estimate soil erosion rates in the Wadi Gazouana Basin using USLE, MUSLE, and RUSLE models. The average soil loss was 9.65, 9.90, and 11.33 t/ha/year for the USLE, MUSLE, and RUSLE models, respectively. The MUSLE model indicated a higher risk of erosion than the other models. The RUSLE model was evaluated as the most suitable model for the study area. The study also found that many soil losses per year could be lower than estimated with the MUSLE model and that short-term, high-intensity runoff caused more soil loss. Previous studies stated that MUSLE did not provide predictive results in estimating the sediment yield for small flows (Williams and Berndt, 1977; Johnson et al., 1985; Sadeghi, 2004; and Sadeghi & Mizuyama, 2007; Ege, 2019).

The uncalibrated WEPP model estimated soil losses was 3.25 t/ha for wheat fields between 1996-2020 in Table 6. The model estimated very high soil losses in 2002, a year with high annual precipitation and wet days. The model estimated the highest surface runoff and soil loss values in January and October, which are the months of soil preparation and plowing for wheat. This situation caused the transport of the plowed soil layer with rain. The model also predicted high soil losses in the winter months due to frequent rains. Similar results were found in previous studies that used the uncalibrated WEPP hillslope model in wheat fields with different slopes in the Tokat region (Demir et al., 2017; Uslu et al., 2022). These results indicate that the WEPP model, even without calibration, can reasonably estimate soil losses in arid regions, especially when the soil is disturbed by tillage practices. Similar results were obtained in previous studies (Kinnell, 2003; Tiwari et al., 2000; Zhang et al.,1996). The model may overestimate soil losses in years with high precipitation because of its sensitivity to surface runoff. The tendency to overpredict smaller events and under predict larger events for both runoff and soil erosion is common in most soil erosion models (Nearing, 1998; Tiwari et al., 2000).For fallow land, soil losses between 1969 and 2020 were estimated using three models (Table 7). The average soil loss estimates of the USLE, MUSLE, and WEPP models are 1.28, 3.45, and 6.24 t/ha, respectively. WEPP and MUSLE did not estimate soil loss, especially in the years when the annual total rainfall was below 500 mm. This is closely related to the duration and intensity of the rainfall in these years. USLE, as in the wheat field, found the lowest soil loss in 1996 and the lowest soil loss in 1995 in the fallow land. USLE estimated high soil loss, especially in the years when heavy rainfall was effective. The WEPP model provided higher estimates compared to the other two models, particularly during years of high rainfall. This can be related to the high peak value of surface runoff. The average annual soil loss values found with the WEPP model show considerable variability. In the years when rainfall was high, the model either did not estimate soil loss or found low estimates. This is closely related to the algorithm of the model. The observed rainfall is not enough to cause soil erosion on bare land.

Conclusion

The observed soil loss data were compared with the simulated USLE, MUSLE, and WEPP models for two periods 1986-1996 and 1969-2020. Soil loss estimates generated by USLE, MUSLE, and WEPP models tend to be higher than actual soil losses. Model performance is also influenced by environmental factors, particularly climate change. . However, predicting the amount and rate of water erosion from land surface into streams and rivers is challenging, expensive and time-consuming, particularly due to the complex land use cover types exist within small scale of lands in Yozgat. The USLE and MUSLE models have been extensively used in Turkey,. The WEPP model is not widely used in Turkey. However, as illustrated by the examples above, its usage has been increasing in recent years. The primary reason for the limited use of the WEPP model is the availability of meteorological data. Specifically, when preparing the CLIGEN file, there is a need for 1, 10, 15, and 30-minute precipitation data. The dataset comprising these values spans many years.

The WEPP model's high estimation of soil losses in both land uses indicates that the uncalibration model's performance is not satisfactory in arid and semi-arid conditions. In summary, these models can be evaluated for performance after being calibrated using more suitable data related to the soil and climate characteristics of the study area. In particular, studies assessing the impact of snowmelt-surface runoff events on soil erosion under different soil management and crop types are crucial for soil conservation.

Declarations

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