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A New Innovative Approach with Revised Pythagorean Fuzzy SWARA in Assessing of Soil Erodibility Factor

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ABSTRACT

Soil erosion is a significant issue that threatens to soil in land degradation processes. The soil erodibility factor is a crucial tool for assessing the susceptibility of soils to erosion. The main aim of this study was to compare the results obtained using the Pythagorean Fuzzy-SWARA method which evaluates the impact weights of the criteria considered for the soil erodibility factor of the soils in the micro-basins located in the district of Çarşamba district of Samsun province, with the results obtained using the formula developed by Wischmeier and Smith. To achieve this case, 78 surface soil samples were collected from micro basins and analyzed for organic matter, clay, sand, silt, very fine sand, degree of structure, and hydraulic conductivity parameters. The erodibility factor was then calculated using these data, and spatial distribution maps were created for both methods. In this study, a revised of the Pythagorean Fuzzy-SWARA approach is proposed to calculate the weight values of the criteria. The values were 0.418 for organic matter, 0.227 for clay, 0.120 for degree of structure, 0.100 for hydraulic conductivity, 0.058 for sand, 0.053 for silt, and 0.039 for very fine sand. Soil erodibility values were determined using a linear combination approach, which normalized all parameter values by a standard scoring function. In estimating soil erodibility, our revised Pythagorean Fuzzy-SWARA approach was found to have a significant relationship with the soil erodibility factor method ($R^2 = 0.691$ at the 1% level) compared to the soil erodibility factor method in estimating soil erodibility. Consequently, the method developed here suggests that fuzzy multi-criteria decision-making methods can be an alternative approach for determining the soil erodibility factor.

Keywords: Soil erodibility, Pythagorean Fuzzy Sets, SWARA, RUSLE-K

1. Introduction

Soil erosion can negatively affect the sustainability of soils in terms of environmental processes, water retention capacities and crop yields, and it is a very critical process in terms of land degradation (Pimentel & Burgess 2013). The intensification of agricultural activities and increasing population can lead to a decrease in soil production capacity and an increase in soil erosion susceptibility rates (Yang et al. 2003; Dotterweich 2013). Soil erosion is influenced by physical factors such as soil sensitivity and properties that affect the separation of soil particles, as well as infiltration, permeability, and water holding capacity (Wischmeier & Smith 1965). The realization of erosion processes due to these properties depends on various soil and environmental factors, including soil organic matter level, texture, slope, and rainfall (Dede et al. 2022).

The Universal Soil Loss Equation (USLE) (Wischmeier & Smith 1978) and the Revised Universal Soil Loss Equation (RUSLE) (Renard et al. 1997) are commonly used to estimate soil erosion worldwide. The erodibility of soils in both equations is determined by the K factor, which is strongly influenced by the physical, hydrological, chemical, mineralogical, and biological properties of soils (Perez-Rodriguez et al. 2007). The consistency of the calculating the soil erodibility factor (RUSLE-K) factor by GIS and geostatistical analyses is based on its potential to represent characteristic variations of soil properties and processes (Saygın et al. 2011). Many studies have used the RUSLE-K factor to the calculate of soil erodibility (Gao et al. 2023; Başkan & Dengiz 2008; Başkan 2022; Beretta & Carrasco-Letelier 2017; Parlak et al. 2014).

Multi-criteria decision-making (MCDM) methods have become increasingly popular in the fields of spatial planning and management. They are now a critical tool for decision-makers, particularly in multi-factor evaluations (Valkanou et al. 2021). Multi-criteria decision-making methods have a wide range of applications and have been used in many studies. They have been used for prioritizing erosion risk areas (Zhang et al. 2020), predicting erosion risk (Demirağ Turan & Dengiz 2017), mapping potential soil erosion (Cartwright et al. 2022), and conducting land suitability studies (Mercan 2023). Zadeh (1965) introduced the concept of fuzzy sets to better express uncertainty, inadequacy, and complexity, which are significant issues in decision-making methods. Yager (2013) continued the development process with Pythagorean Fuzzy Sets (PFSs). When defining PFSs, it was determined that the sum of the squares of the degrees of membership and non-membership of the set should not exceed 1. This structure enables decision-makers to make evaluations from a broader perspective. The SWARA method, developed by Keršulienė et al. (2010), enables the determination of criteria weights by considering the priority rankings determined by decision-makers. Pairwise comparisons are made between the criteria by taking into account expert opinions. Several studies in the literature integrate PFSs to SWARA method. Rani et al. (2020) used the Pythagorean Fuzzy-SWARA (PF-SWARA) and VIKOR integration for performance evaluation of solar panel selection, Kamali Saraji et al. (2022) used PF-SWARA and TOPSIS integration in the evaluation of sustainable energy development processes of European Union countries, Rani et al. (2020) used PF-SWARA ARAS method to evaluate healthcare waste treatment, Saeidi et al. (2022) used PF-SWARA and TOPSIS integration in the evaluation of sustainable human resources management.

In the above-mentioned studies, experts were asked to rate a set of pre-defined criteria using a scale to determine the weighting in the PF-SWARA approaches. The resulting score function values were ranked from highest to lowest and then used in the SWARA method by subtracting the criteria from each other, rather than through pairwise comparisons. However, it is important to note that the SWARA method ranks criteria based on their importance degrees within the scope of expert opinions, without making pairwise comparisons for each criterion. This may lead to different interpretations of the results obtained. To prevent such interpretation differences, this study proposes a new innovative approach to the PF-SWARA method.

In this context, the present study uses the revised PF-SWARA approach to calculate the soil erodibility of the micro-basins located in Çarşamba district of Samsun province This approach evaluates the formula and criteria developed by Wischmeier and Smith through pairwise comparisons. The current study also aims to create spatial distribution maps and compare the obtained results. Furthermore, the revised PF-SWARA approach was applied for the first time to the soil erodibility factor, thus it has the potential to make a significant contribution to this field of study and the existing literature.

2. Material and Methods

The study area is situated in the eastern part of Samsun Province of Türkiye and the western part of Ordu Province, covering an area of 1037.7 km^2. It is located between the east coordinates of 296 000-316 000 and the north coordinates of 4 549 000-4 577 000 (Universal Transverse Mercator-UTM, WGS-84, Zone-37), with an elevation ranging from 0 to 416 m above sea level (Figure 1). The selected study area lies south of the town Samsun-Çarşamba district on the edge of the Çarşamba delta plain, including both a part of the lowland and hills and extends around the accumulation lake on the Yeşilırmak River that passes through the middle of our study.

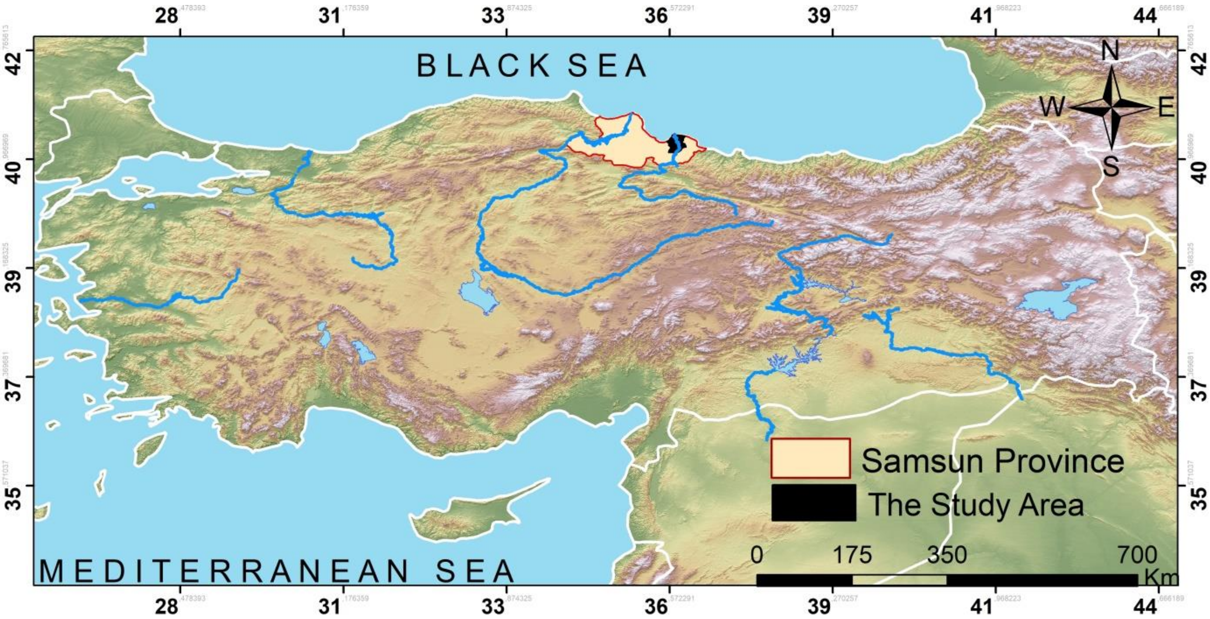

Figure 1- Location map of the study area

According to meteorological data collected by the Turkish State Meteorological Service (DMI) between the years 1960 and 2017, the climate in Çarşamba district is semi-humid with average annual precipitation and evapotranspiration levels being 1023 mm and 772 mm. The average annual temperature is 14.4 °C, average temperature in July is 23.3 °C and in January 6,4 °C. As calculated in the study by Miháliková & Dengiz (2019), the Newhall simulation model classifies the soil climate of the study area as having a mesic soil temperature regime and udic (subgroup: dry tempudic) moisture regime. Besides, Bölük (2016) reports that the study area is classified as "very moist," with a precipitation activity index of 66.64 scores based on the macroclimate regions of Erinc in Türkiye.

The general slopes of the study area's the flat and nearly flat lands of the study area are in the south-north direction and average 0.1%. This slope decreases to 0.0 - 0.02% as it approaches the seaside. On the slope lands towards the south, the slope varies between 2 - 40% (Figure 2). Although the climatic conditions of the plain are suitable for cultivating many crops, the high level of groundwater, surface drainage needs, lack of irrigation water, leveling disorders, and consolidation needs have an adverse effect on the crop pattern and yield.

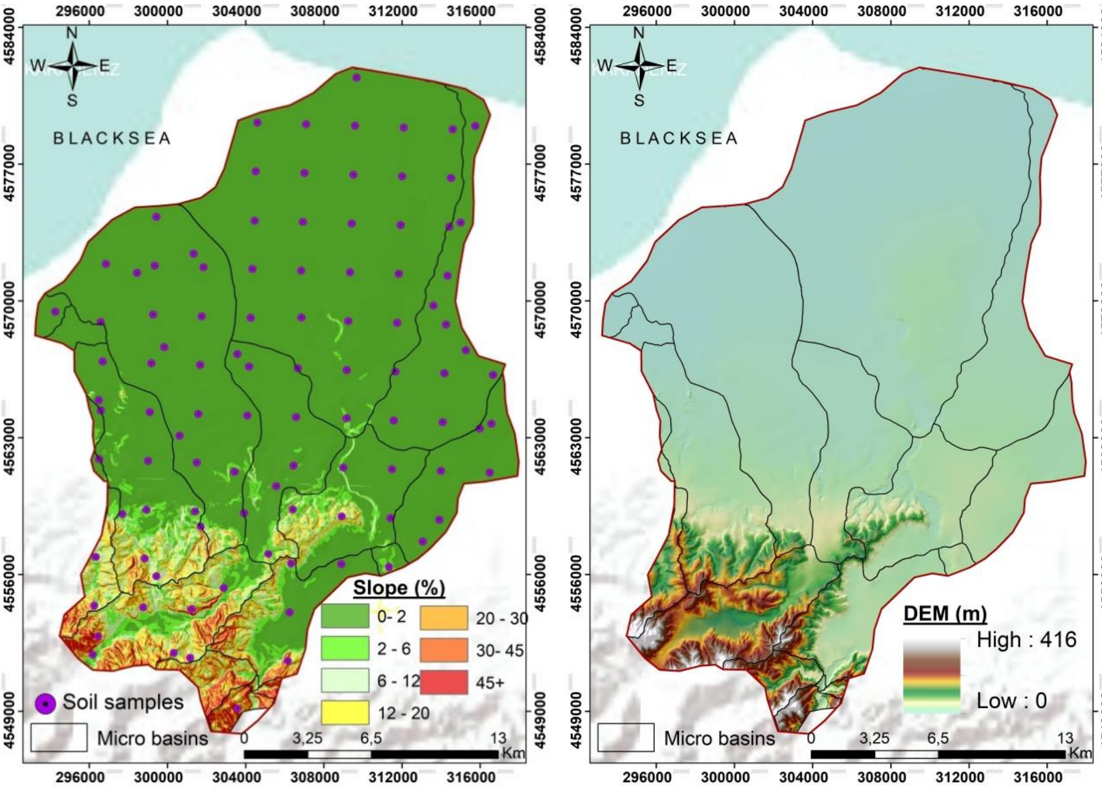

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Figure 2- Slope, elevation and soil sampling pattern maps

2.1. Soil sampling and analysis

Within the scope of the study, 78 soil samples were collected from micro basins located within the borders of Çarşamba district of Samsun province. The samples were taken from 0-30 depth cm in an area with a semi-humid ecosystem (refer to Figure 2). This study used Bouyoucos (1962) to determine the textural content of the soils, the Walkley-Blake method (Jackson 1958) to determine the organic matter content, Klute & Dirksen's (1986) method to determine saturated hydraulic conductivity, and the wet sieving method under laboratory conditions to determine the very fine sand content. To perform Very fine sand analysis, 10 g of soil must first be crushed with chemical (calgon) and mechanical (mixer). It must then be sieved through a 0.105 mm, after which the percentage of coarse sand can be determined from the remaining dry particles. The percentage of fine sand is calculated by subtracting the percentage of coarse sand from the total percentage of sand obtained by texture analysis (Wischmeier & Smith 1978). The RUSLE-K factor was then determined, and the soil structure classes were determined according to Wischmeier & Smith (1978).

2.2. Soil erodibility (RUSLE-K)

The following formula developed by Wischmeier & Smith (1978) is used to determine the susceptibility of soils to erosion.

$$100 * K = ((2.1 \times 10^{-4}) \times (12 - OM) \times M^{1.14} + 3.25 \times (S - 2) + 2.5 \times (P - 3))/d \quad (1)$$

In the equation; K: Soil erodibility factor, M: Particle size parameter, OM: Organic matter content, %, S: Structure type code, P: Hydraulic conductivity, d: Conversion coefficient to metric system (d=7.59)

The following equation was used to determine the particle size (M) parameter in the equation.

$$M = (\%\, Very\, fine\, sand + \%\, Silt) \times (100 - \%\, Clay) \quad (2)$$

The RUSLE-K equation used in this study is valid only when the organic matter is less than 4%. For this reason, instead of excluding the data of 12 soil samples in our study, it was used by limiting it to 4% (Efthimiou 2018).

2.2. Pythagorean fuzzy set theory preliminary definition

PFSs were first introduced by Yager in 2013 and were developed as an extension of Intuitionistic Fuzzy Sets (IFSs) to offer decision-makers a wider scope in defining uncertainties (Yager 2013). When determining IFSs, the sum of the membership and non-membership degrees cannot be greater than 1. Still, when when defining uncertainty in PFSs, the sum of the squares of the membership and non-membership degrees is determined to not exceed 1. This condition enables PFSs to cover a much wider area in defining uncertainties (Fgure 3).

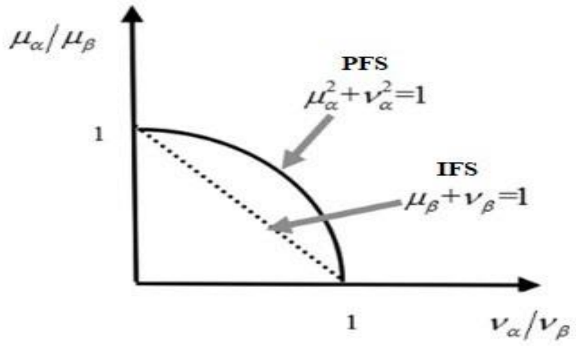

Figure 3- Formal expression of PFSs and IFSs (Peng and Yang, 2016)

The following equations are used to define PFSs (Yager 2013).

$$P = \{x, \mu_p(x), v_p(x);\ x \in X\} \quad (3)$$

Where, $\mu_p: X \to [0,1]$ defined with the degree of membership, $v_p: X \to [0,1]$ defined with the degree of non-membership. In here, $\mu_p(x)$, $v_p(x) \in [0,1]$ and is described as

$$0 \leq (\mu_p(x))^2 + (v_p(x))^2 \leq 1 \quad (4)$$

Eq. 5 is used to determine the hesitation degrees of PFSs.

$$\pi_p(x) = \sqrt{1 - (\mu_p(x))^2 + (v_p(x))^2} \quad (5)$$

Where, πp is hesitation degrees.

Arithmetic operations for two PFSs are stated in the equations below. It is assumed that $\beta_1 = P(\mu_{\beta 1}, v_{\beta 1})$ and $\beta_2 = P(\mu_{\beta 2}, v_{\beta 2})$ two PFSs.

$$\beta_1 \oplus \beta_2 = P(\sqrt{\mu_{\beta 1}^2 + \mu_{\beta 2}^2 - \mu_{\beta 1}^2\mu_{\beta 2}^2}, v_{\beta 1}v_{\beta 2}) \quad (6)$$

$$\beta_1 \otimes \beta_2 = P(\mu_{\beta 1}\mu_{\beta 2}, \sqrt{v_{\beta 1}^2 + v_{\beta 2}^2 - v_{\beta 1}^2 v_{\beta 2}^2}) \quad (7)$$

$$\lambda\beta = P(\sqrt{1 - (1 - \mu_\beta^2)^\lambda}, (v_\beta)^\lambda) \quad (8)$$

$$\beta^\lambda = P((\mu_\beta)^\lambda, \sqrt{1 - (1 - v_\beta^2)^\lambda}) \quad (9)$$

The equations used to determine the score and uncertainty functions of PFSs are (Zhang & Xu 2014);

$$S(\beta) = (\mu_\beta)^2 - (v_\beta)^2, \hbar(\beta) = (\mu_\beta)^2 + (v_\beta)^2, \text{ here} S(\beta) \in [-1,1] \text{ and } \hbar(\eta) \in [0,1] \tag{10}$$

Where; S(β): the score function and $\hbar(\eta)$: uncertainty function.

Where; since the score (S) function is between [-1, 1], equation 11 is used when calculating the normalized form of the values and the degree of uncertainty (Wu & Wei 2017).

$$S*(\beta) = \frac{1}{2}(S(\beta)+1), \hbar^{o}(\beta) = 1 - \hbar(\beta), \text{ so that } S*(\beta), \hbar^{o}(\beta) \in [0,1]. \tag{11}$$

Where; S*(β): normalized score function, $\hbar^{o}(\beta)$: degree of uncertainty.

2.3. The why proposed pythagorean fuzzy SWARA approach

It is well known that MCDM methods are an important tool that takes into account the opinions of decision makers in solving any complex problem in last decades. It can be also mentioned that SWARA method is used by Kerŝulienė et al. (2010) as a method in which we can obtain weight by ranking the criteria according to their importance in solving critical problems. The method allows decision-makers to choose their own priorities by taking into account the conditions in terms of the problem (Zavadskas et al. 2019). On the other hand, the area of use of the SWARA method has been expanded by using it in many fuzzy set studies used to identify uncertainties. In the PF-SWARA method, which is widely used in the literature, each criterion in the problem is evaluated by taking expert opinions with PFSs and the criteria are ranked from the highest to the lowest by calculating the score values. The score values obtained after the criteria ranking are not subjected to the pairwise comparison process, which is a stage of the classic SWARA method, and instead, the score values are subtracted from the score value below and the resulting value is processed in the SWARA method (Rani et al. 2020; Saeidi et al. 2022; Kamali Saraji et al. 2022). Here, although there is a score value initially obtained with PFSs, since each criterion is evaluated within each criterion instead of pairwise comparison, it causes the desired results for the problem not to be obtained in the criterion weights obtained with the SWARA method afterward.

This study was used the revised PF-SWARA method to determine the criterion weights. With the method we propose within the scope of our study, the criteria are ranked according to their importance, taking into account expert opinions. Scale evaluation is then performed using PFSs clusters. Here, pairwise comparisons in the evaluation of criteria are made using PFSs. The score function obtained by making pairwise comparisons is then used to calculate the criterion weights. Although it is similar to the traditional SWARA method (Kerŝulienė et al. 2010) in terms of method, the PFSs approach used in the evaluation of the criteria distinguishes the study from other methods (Rani et al. 2022; Kamali Saraji et al. 2022; Saeidi et al. 2022) and offers a new approach to the literature. The stages of the revised PF-SWARA method are stated below.

Step 1: First of all, experts are evaluated with the help of the scale in Table 1, taking into account their work history and expertise on the subject.

Table 1- Scale for evaluating the performance of experts (Cui et al. 2021)

Linguistic expressions	*PFNs* (μ, v, π)
Extremely important (EI)	(0.90, 0.15, 0.409)
Very very important (VVI)	(0.75, 0.40, 0.527)
Very important (VI)	(0.70, 0.55, 0.456)
Important (I)	(0.60, 0.70, 0.387)
Less important (LI)	(0.40, 0.80, 0.447)
Very less important (VLI)	(0.30, 0.90, 0.316)

μ: membership degree, v: non-membership degree, π: hesitation degree

Step 2: The following equation (Eq. 12) is used to calculate the weights of experts. Calculating expert weights is very important for MCDM processes. Here, let $E_k=\gamma(\mu_k, v_k)$ be in the PFN of k experts, while calculating the weight of this expert;

$$\omega_k = \frac{(\mu_k^2+\pi_k^2\times(\frac{\mu_k^2}{\mu_k^2+v_k^2}))}{\sum_{k=1}^{\ell}(\mu_k^2+\pi_k^2\times(\frac{\mu_k^2}{\mu_k^2+v_k^2}))}, k=1(1)\ell; \omega_k \geq 0, \sum_{k=1}^{\ell}\omega_k = 1 \tag{12}$$

Where; k represents the decision expert, w: the weight of k[th], μ: membership degree, v: non-membership degree, π: hesitation degree and ℓ: total number of the experts.

Step 3: The criteria are ranked from highest to lowest according to their importance, taking into account expert opinions before pairwise comparisons.

Step 4: At this stage, normalized score function values were obtained by making a pairwise comparison of the criteria determined according to their importance level with the criterion in the lower row. The linguistic expressions used by experts to evaluate the criteria within the scope of the study are listed in Table 2.

Table 2- Linguistic expressions used for expert opinions (Saeidi et al. 2022)

Linguistic expressions	*PFNs* (μ, v, π)
Absolutely high (AH)	(0.95, 0.20, 0.387)
Very very high (VVH)	(0.85, 0.30, 0.433)
Very high (VH)	(0.80, 0.35, 0.487)
High (H)	(0.70, 0.45, 0.554)
Medium high (MH)	(0.60, 0.55, 0.581)
Medium (M)	(0.50, 0.60, 0.624)
Medium low (ML)	(0.40, 0.70, 0.592)
Low (L)	(0.30, 0.75, 0.589)
Very low (VL)	(0.20, 0.85, 0.487)
Absolutely low (AL)	(0.10, 0.95, 0.296)

μ: membership degree, v: non-membership degree, π: hesitation degree

Step 5: At this stage, the most important criterion in calculating the k_j value is determined as 1, and +1 is added to each score value below it (Eq. 13) (Keršulienė et al. 2010).

$$k_j = \begin{cases} 1 & ,j=1 \\ s_j+1 & ,j>1 \end{cases} \tag{13}$$

Where; kj is relative coefficient and sj presents the comparative significance of score value.

Step 6: In this step, the importance vector is calculated and, as stated in the previous equation, the most important criterion is 1, and the importance vectors for other criteria are determined by dividing the previous importance vector to the criterion coefficient (Eq. 14).

$$q_j = \begin{cases} 1 & j=1 \\ \frac{q_{(j-1)}}{k_j} & ,j>1 \end{cases} \tag{14}$$

Where; q_j is the weight of the importance vector.

Step 7: The final weights of the criteria are obtained by dividing the weight of the importance vectors obtained in the previous step by the sum of the importance vector weights as stated in Eq. 15. The m value here represents the number of criteria.

$$w_j = \frac{q_j}{\sum_{j=1}^{m} q_j} \tag{15}$$

Step 8: Within the scope of the study, the criterion weights in the study are calculated for each expert by following the above steps. In the next stage, the sum of the values obtained by multiplying the expert weights obtained within the scope of evaluating the experts and the criterion weights obtained from the experts is taken and the criterion weights are calculated.

2.4. Normalization process with a standard scoring function

Soil erodibility factor is determined by considering soil parameters such as organic matter content, texture, degree of structure, permeability, and very fine sand properties (Wischmeier & Smith 1978; Renard et al. 1997). All parameters used in the calculation of soil erodibility factor were calculated under laboratory conditions in this study. At this stage, the standard scoring function was used to normalize the values of soil parameters and assign scores ranging from 0 to 1 due to differences in soil parameter units (Andrews et al. 2002). The scoring function enables the considers of low, high, and average levels of the desired feature within the study's scope (Liebig et al. 2001). Two different scoring functions were used to ensure a linear correlation between the score values used in estimating soil erodibility and the soil erodibility obtained by the formula developed by Wischmeier & Smith (1978). The 'Less is better' (LB) function was utilized to determine the soil's organic matter content, clay, structural stability, and saturated hydraulic conductivity values. For the sand, silt and very fine sand properties of the soils, the "more is better-MB" function was used (Table 3).

Table 3- Standard scoring functions for K parameters (Eqs. 16-17)

Parameters	*SF*	*L*	*U*	*Standard Scoring Function Equation*
Organic matter	LB	0.50	4.00	$f(x) = \begin{cases} 0.1 & , x \leq L \\ (1-(0.9)*(\frac{x-L}{U-L})), & L \leq x \leq U \\ 1 & , x \geq U \end{cases}$ (16)
Clay	LB	6.44	63.53	
Structure degree	LB	1.00	3.00	
Hydraulic conductivity	LB	0.07	7.31	
Sand	MB	7.33	77.93	$f(x) = \begin{cases} 0.1 & , x \leq L \\ (0.1+(0.9)*(\frac{x-L}{U-L})), & L \leq x \leq U \\ 1 & , x \geq U \end{cases}$ (17)
Silt	MB	13.81	53.9	
Very fine sand	MB	5.05	24.69	

SF: Score Function, MB: more is better, LB: less is better. L and U are the lower and upper thresholds, respectively

After the determination of the weights of the relative importance levels of soil erodobility parameters by the revised PF-SWARA method and the normalized values obtained from the standard scoring function, the Weighted Linear Combination (WLC) method was used to determine the erodobility levels of the soils. WLC is also known as simple additive weighting (SAW), weighted summation, weighted linear average and weighted overlay (Malczewski & Rinner, 2015). The WLC method calculates the soil erosion susceptibility value using the formula in Eq. (18).

$$\text{PF SWARA} - \text{K} = \sum_{k=1}^{l} \omega_k * a_{ik} \quad (18)$$

Where; ω_k is the criteria weights obtained from the revised PF-SWARA method, a_{ik} is the normalized standard value of the parameter k obtained from the standard scoring function, and l is the total number of criteria.

2.5. Determination of spatial distributions

After the calculating the criterion weights and score values obtained for each parameter using the weighted linear combination method, interpolation methods were used to generate a map of the estimated soil erodibility. The values were calculated using the RUSLE-K method. In mapping the obtained coordinated point values, the inverse distance weighting (IDW) method, which uses a linear combination of weightings at known points to estimate the value at an unknown point, was considered. Teegavarapu & Chandramouli (2005) found that IDW predicts attribute values at unsampled points by adding the values at sampled points, weighted by an inverse function of the distance from the point of interest to the sampled points. The IDW approach assumes that the value of a point is more influenced by closer points than by those further away. Predictions were determined using the Eq. (19):

$$Z = [\sum_{i=1}^{n} (Z_i / d_i^m) / \sum_{i=1}^{n} (1/d_i^m)] \quad (19)$$

Where; Z is the estimated value, Z_i is the measured sample value at point i, d_i is the distance between Z and Z_i, and m is the weighting power that describes the ratio at which weights fall off with d_i. The study compared the IDW predictions using the common 1, 2, and 3 weighting powers (Pirmoradian et al. 2010; Keshavarzı and Sarmadian 2012).

Comparative statistics (Spearman's correlation) between parameters and descriptive statistics such as average, minimum, maximum, standard deviation, coefficient of variation, kurtosis and skewness obtained within the scope of the study with using IBM SPSS Statistics 23v. software (IBM Corp 2015).

3. Results and Discussion

3.1. Investigation of soil erodibility parameters and correlation relationship

In a total of 78 coordinated soil samples taken from the study area, the parameters used to determine the erodibility of the soils were calculated and the descriptive statistics of RUSLE-K and PF SWARA-K obtained by using these parameters are given in Table 4. The clay content of the soils varied between 6.4 % and 63.5 %, sand content between 7.3 % and 77.9 % and silt content between 13.8 % and 53.9 % and they were generally classified as medium textured. In addition, very fine sand contents, which are used to determine the susceptibility of soils to erosion, were found to vary between 5.1 % and 24.7 %.

The RUSLE-K values were calculated using the formula developed by Wischmeier & Smith (1978), ranging between 0.008 and 0.049. Meanwhile, the K factor was calculated using the revised PF-SWARA method, ranging between 0.260 and 0.874. The coefficients of variation of the parameters used in the study were evaluated according to Wilding's (1985) classification system. It was emphasized that coefficients of variation are low for values less than 15%, medium for values between 15% and 35%, and high for values above 35%. Upon analyzing the coefficients of variation of the soil samples, it was determined that the degree of structure had a low coefficient of variation at 12%. In comparison, the percentage of sand and hydraulic conductivity values had high variability at 55.9% and 156.8%, respectively. The soils' organic matter content ranged from 0.5% to 4%, with moderate variability (coefficient of variation of 34.4%).

Table 4- Descriptive statistics values of the parameters

Parameters	*Mean*	*SD*	*Variation*	*CV.*	*Min.*	*Max.*	*Skewness*	*Kurtosis*
RUSLE-K	0.030	0.008	0.000	27.43	0.008	0.049	-0.137	0.369
PF SWARA-K	0.468	0.133	0.018	28.42	0.258	0.871	-0.328	0.557
OM (%)	2.678	0.922	0.849	34.41	0.503	4.000	-0.836	-0.191
Clay (%)	41.084	11.225	126.011	27.32	6.438	63.534	-0.234	-0.202
Sand (%)	23.762	13.282	176.412	55.89	7.333	77.928	2.737	1.446
Silt (%)	35.154	7.908	62.537	22.49	13.807	53.903	0.163	-0.199
H.C (cm/h)	0.524	0.822	0.675	156.78	0.071	7.307	62.215	7.534
S.D (unitless)	2.885	0.360	0.129	12.46	1.000	3.000	11.068	-3.275
Vfs (%)	13.842	4.664	21.749	33.69	5.048	24.689	-0.516	0.316

SD: standard deviation, Min.: minimum, Max.: maximum, n: sample number (78), CV (coefficient of variation): <15 = low variation, 15–35 = moderate variation, >35 = high variation, Skewness:< │ +- 0.5 │ = normal distribution, 0.5–1.0 = application of character changing for dataset, and >1.0 → application of Logarithmic change, Vfs: Very fine sand, OM: Organic matter, H.C: Hydraulic conductivity, S.D: Structure degree

In the present study, Spearman's correlation analyses were performed for all parameters as well as pairwise comparisons of RUSLE-K obtained from real values and K factor obtained by PF-SWARA method (Table 5). The statistically significant value of 0.691** (P<0.01) between the soil erodibility factor calculated using the PF-SWARA method and the values calculated with the RUSLE-K method is an important result in terms of the success of the applied method. Here, instead of looking at the pairwise comparisons between all parameters, examining the importance of the criteria used in the calculating soil erodibility in terms of PF SWARA-K and RUSLE-K would be more accurate. For instance, both methods yielded significant results at the 1% level for very fine sand, clay, and hydraulic conductivity values, and the correlation values were similar. The study's most significant difference is that organic matter is -0.579** for RUSLE-K and -0.917** for PF SWARA-K. Therefore, organic matter is a more critical parameter for our newly developed method. Previous studies have shown that organic matter plays a crucial role in supporting aggregate structures in soils, which results in a reduction in soil erodibility (Dede et al. 2022; İmamoğlu & Dengiz 2017).

Table 5- Correlation values between model outputs and parameters

Parameters	*RUSLE-K*	*PF SWARA-K*	*Vfs*	*Clay*	*Sand*	*Silt*	*OM*	*H.C*	*S.D*
RUSLE-K	1								
PF SWARA-K	0.691**	1							
Vfs	0.477**	0.336**	1						
Clay	-0.562**	-0.659**	-0.457**	1					
Sand	0.250*	0.416**	0.655**	-0.789**	1				
Silt	0.636**	0.251*	-0.147	-0.194	-0.346**	1			
OM	-0.579**	-0.917**	-0.193	0.351**	-0.153	-0.198	1		
H.C	0.320**	0.343**	0.299**	-0.874**	0.622**	0.234*	-0.021	1	
S.D	0.148	-0.322**	-0.037	0.457**	-0.444**	0.191	0.149	-0.431**	1

*: Correlation is significant at 0.05. **: Correlation is significant at 0.01 level. Vfs: Very fine sand, OM: Organic matter, H.C: Hydraulic conductivity, S.D: Structure degree

3.2. Weighting of soil erodibility criteria by revised PF SWARA method

The criteria used in the RUSLE-K calculation of soil erodibility, including organic matter, clay, sand, silt, very fine sand, hydraulic conductivity, and degree of structure, were also used to determine the criteria weights by the revised PF SWARA method. The opinions of three expert agricultural engineers experienced in soil science, particularly erosion, were consulted for this study. The weights of the experts were determined based on their level of experience in the field. Each expert was evaluated using the scale provided in Table 1, and the resulting expert weights are presented in Table 6.

Table 6- Weights of experts evaluating the criteria

Experts	*Linguistic Expressions*	μ	ν	π	*Expert Weights*
Expert 1	VI	0.7	0.55	0.456	0.372
Expert 2	VI	0.7	0.55	0.456	0.372
Expert 3	I	0.6	0.7	0.387	0.255

μ: membership degree, ν: non-membership degree, π: hesitation degree

In this study, the revised PF SWARA approach prioritize each criterion based on expert opinions using the traditional SWARA approach. Pairwise comparisons between each prioritised criterion and the one below are determined using PFNs. Expert opinions were obtained using the scale provided in Table 2, and the resulting linguistic expressions are presented in Table 7.

Table 7- Linguistic expression of the criteria in line with expert opinions

Criteria	*Expert 1*	*Expert 2*	*Expert 3*
OM (%)			
Clay (%)	AH	VVH	VH
S.D (Unitless)	VVH	AH	AH
H.C (cm/h)	VL	L	VL
Sand (%)	VH	VVH	H
Silt (%)	VL	AL	AL
Vfs (%)	M	ML	L

Vfs: Very fine sand, OM: Organic matter, H.C: Hydraulic conductivity, S.D: Structure degree; Absolutely high (AH), Very very high (VVH), Very high (VH), High (H), Medium high (MH), Medium (M), Medium low (ML), Low (L), Very low (VL), Absolutely low (AL)

The score function was calculated using the linguistic expressions obtained from pairwise comparisons, with Eqs. (10-11) (Table 8). Once the score function values were obtained through the use of PFSs in pairwise comparisons, the process of determining the criteria weights began.

Table 8- Expression of the score values of the criteria according to expert opinions

Criteria	*Expert 1* (μ, v)	*Expert 2* (μ, v)	*Expert 3* (μ, v)	*1st. Crisp Values*	*2st. Crisp Values*	*3st. Crisp Values*
OM (%)						
Clay (%)	(0.95, 0.20)	(0.85, 0.30)	(0.80, 0.35)	0.931	0.816	0.759
S.D (Unitless)	(0.85, 0.30)	(0.95, 0.20)	(0.95, 0.20)	0.816	0.931	0.931
H.C (cm/h)	(0.20, 0.85)	(0.30, 0.75)	(0.20, 0.85)	0.159	0.264	0.159
Sand (%)	(0.80, 0.35)	(0.85, 0.30)	(0.70, 0.45)	0.759	0.816	0.644
Silt (%)	(0.20, 0.85)	(0.10, 0.95)	(0.10, 0.95)	0.159	0.054	0.054
Vfs (%)	(0.50, 0.60)	(0.40, 0.70)	(0.30, 0.75)	0.445	0.335	0.264

Vfs: Very fine sand, OM: Organic matter, H.C: Hydraulic conductivity, S.D: Structure degree. µ: membership degree, v: non-membership degree, π: hesitation degree

The score functions obtained within the scope of the study were used to calculate the k_j value with the help of Eq. (13). Here, the most important criterion is accepted as 1 and k_j value is calculated by adding +1 to each criterion in the lower step. In the calculating the importance vector (q_j) value, the importance vectors of the other criteria were determined by dividing the previous importance vector by the k_j coefficient as shown in Eq. 14, again taking the most important criterion as 1. Due to the high number of steps, only the calculations made for expert 1 are shared in this section (Table 9).

Table 9- Calculation of criterion weights according to expert 1 opinions

Criteria	s_j ** Crisp Values*	k_j	q_j	w_j
OM (%)		1.000	1.000	0.418
Clay (%)	0.931	1.931	0.518	0.216
S.D (Unitless)	0.816	1.816	0.285	0.119
H.C (cm/h)	0.159	1.159	0.246	0.103
Sand (%)	0.759	1.759	0.140	0.058
Silt (%)	0.159	1.159	0.121	0.050
Vfs (%)	0.445	1.445	0.084	0.035

Sj: the comparative significance of score value, kj: relative coefficient, qj: the weight of the importance vector, Wj: the final weight of criteria.

Then, the criteria weights were calculated for the other experts and the weights obtained as a result of the evaluations of all experts are given in Table 10. In the last column of Table 10, the aggregated criteria weights calculated by multiplying the expert weights of 0.372, 0.372 and 0.255 calculated in the first stage of the PF-SWARA method with the weights obtained from the criteria are given.

When the criteria weights calculated by the PF-SWARA method are examined, it is observed that the highest criterion weight is 0.418 for organic matter. Subsequently, the weights of criteria considered important for soil erodibility, namely clay, structure degree, and hydraulic conductivity, are obtained as 0.227, 0.120, and 0.100, respectively. In terms of the study, it is seen that the criteria levels of sand, silt, and very fine sand have less importance with weights of 0.058, 0.053, and 0.039, respectively. Pacci et al. (2023) conducted a study to calculate the criterion weights of erosion sensitivity parameters using the fuzzy analytic hierarchy process approach. The study found that organic matter, bulk density, and clay had the highest criterion weights of 0.317, 0.224, and 0.264, respectively. These criterion weights were similar to those obtained with the revised PF-SWARA approach for organic matter and clay levels.

Table 10- Aggregated criterion weights of criteria

Criteria	*Expert 1*	*Expert 2*	*Expert 3*	*Aggregated Criterion Weights*
OM	0.418	0.418	0.418	0.418
Clay	0.216	0.230	0.238	0.227
S.D	0.119	0.119	0.123	0.120
H.C	0.103	0.094	0.106	0.100
Sand	0.058	0.052	0.065	0.058
Silt	0.050	0.049	0.061	0.053
Vfs	0.035	0.037	0.049	0.039

3.3. Spatial distributions of soil erodibility factor for both approaches

The normalized values of the soil properties obtained from the analysis results with the standard scoring function were used to calculate soil erodibility by the WLC technique, in line with expert opinions on determining of criteria weights for the parameters considered in the study. The calculation of soil erodibility was based on each criterion analyzed (Patrono 1998; Çakır & Dengiz 2021). Distribution maps were generated using the RUSLE-K method, which is utilized to obtain soil erodibility factor, and values obtained from our developed PF SWARA-K approach, as well as the IDW method. The distribution maps obtained from the traditional RUSLE-K method for estimating soil erodibility showed parallelism with those obtained from the PF SWARA-K method, with a statistically significant relationship at the 1% level (0.691**). When examining the spatial distributions of soil erodibility values, sensitive areas to soil erosion are observed in the central regions in both prediction methods (Figure 3). It is observed that similar results are obtained for both parameters and soil erodibility increases as the coastal areas are approached.

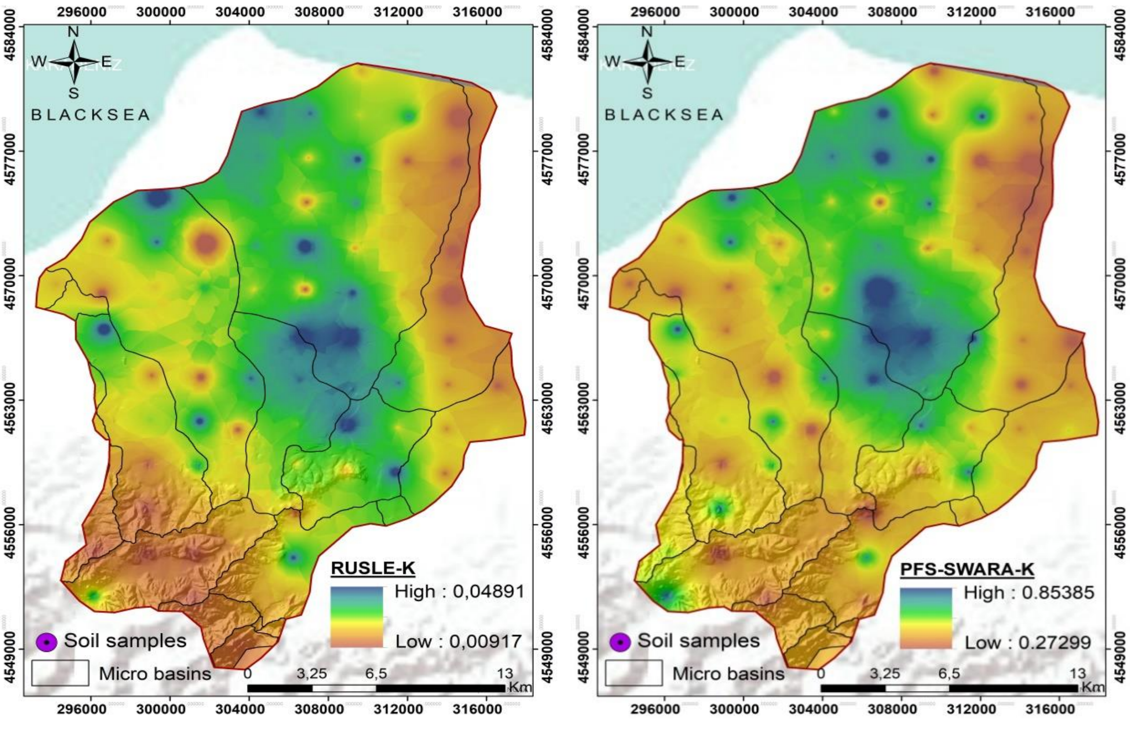

Figure 3- Distribution maps of RUSLE - K and PF SWARA-K

4. Conclusions

The soil erodibility factor is an important parameter used to determine the sensitivity of soils to erosion. It can be said that the erodibility factor in prediction models such as USLE and RUSLE used in erosion studies has been calculated with different applications in different studies (Delgado et al. 2023; Pontes et al. 2022; Panagos et al. 2014) and the studies conducted in terms of literature are accepted.

The present study, it was aimed to compare the RUSLE-K factor calculated by traditional methods with PF-SWARA and distribution maps in an area located in the micro-basins of Çarşamba district of Samsun province of Central Black Sea. All parameters used in the traditional method were used as the basis for the determination of the criteria for the proposed approach. On the other hand, the main approach of in the PF SWARA-K method was considered expert knowledge approach considered the contribution and effect of the considered parameters on soil erosion susceptibility. As a result of the study, it was observed that the revised PF SWARA-K method obtained significant results at 1% level with 0.691** compared to the RUSLE-K factor calculated by traditional methods. As a result, it can be said that the fuzzy-multi criteria decision methods are an alternative approach that can be used in determining the soil erodibility factor. These results which we obtained with the expert opinions used in determining the criteria weights are likely to obtain much better results with the improvements to be made in the importance levels of the criteria and expert opinions in future studies. In addition, this study was carried out in an area with a semi-humid-humid ecological characteristic, and it is recommended to carry out studies in areas with different ecological characteristics.

Statements & Declarations

Ethical Approval:

We hereby would like to warrant that the manuscript represents original work that is not being considered for publication, in whole or in part, in another journal, book, conference proceedings, or government publication with a substantial circulation. I would like to warrant that all previously published work cited in the manuscript has been fully acknowledged. In addition, our manuscript has not been submitted to a preprint server prior to submission on any journal.

Competing Interest

Financial interests: All authors declare that they have no financial interests.

Conflict of Interest Statement:
The authors declare that they have no conflict of interest related to the content of this manuscript. The authors have no relevant financial or non-financial interests to disclose

Data Availability Statement:

The datasets generated and analysed during the current study are not publicly available but are available from the corresponding author on reasonable request.

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Authors' contributions:

All authors contributed to the study conception and design. Methodology, Conceptualization and Resources were done by Orhan Dengiz, Aykut Çağlar and Barış Özkan. Supervision was performed by Orhan Dengiz. Material preparation, investigation and analysis were performed by Aykut Çağlar and Barış Özkan. All maps created by Orhan Dengiz. The first draft of the manuscript was written by Orhan Dengiz, Aykut Çağlar and Barış Özkan commented on previous versions of the manuscript. All authors read and approved the final manuscript

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