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Predicting the spatial distribution of soil erodibility factor using USLE nomograph in an agricultural watershed, Ethiopia

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Abstract

Soil erosion in the northwestern Amhara region, Ethiopia has been a subject of anxiety, resulting in a major environmental threat to the sustainability and productive capacity of agricultural areas. This study tried to estimate soil erodibility factor (*K*-factor) using Universal Soil Loss Equation (USLE) nomograph, and evaluate the spatial distribution of the predicted *K*-factor in a mountainous agricultural watershed. To investigate the *K*-factor, the 54 km^2 study watershed was divided into a 500 m by 500 m square grid and approximately at the center of each grid, topsoil samples (roughly 10 to 20 cm depth) were collected over 234 locations. Sand, silt, clay and organic matter (OM) percentage were analyzed, while soil permeability and structure class codes were obtained using the United States Department of Agriculture (USDA) document. The resulting coefficient of variation (CV) of the estimated *K*-factor was 0.31, suggesting a moderate variability. Meanwhile, the value of nugget to sill ratio of *K*-factor was 0.32, which categorized as moderate spatial autocorrelation. Prediction accuracy and model fitting effect of the Gaussian semivariogram approach was best, suggesting that the Gaussian ordinary Kriging model was more appropriate for predicting *K*-factor. The resulting value of the mean error (ME) was 0 and the mean squared deviation ratio (MSDR) was nearly 1, which indicates the Gaussian model was unbiased and reproduced the experimental variance sufficiently. The values of *K*-factor were smaller (0.0217 to 0.0188) in the northern part and gradually increased (0.0273 to 0.033 Mg h MJ^{-1} mm^{-1}) towards the central and south of the study watershed.

Keywords: Nomograph; Semivariogram; Soil erodibility factor; Spatial variability; Watershed

1. Introduction

Globally, soil erosion is a principal degradative process (Zhu, Li, Li, Liu & Xue, 2010) resulting in a negative impacts on different soil functions (food and other biomass production, water storing, filtering and transformation, habitat and gene pool, physical and cultural environment for mankind, and source of raw materials) (Dorren et al., 2004), which ultimately causes irreversible effect on the poorly renewable soil resource (Buttafuoco, Conforti,

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Aucelli, Robustelli & Scarciglia, 2012). Soil erosion is the major cause of soil degradation in Ethiopia, especially in northwestern highlands of Amhara Region (Amare et al., 2014). In the Ethiopia highlands, soils are often more exposed to erosion largely due to cultivation of the steep and fragile soils, limited recycling of dung and crop residues, deforestation and overgrazing (Habtamu, Heluf, Bobe & Enyew, 2014), poor soil management (Amare et al., 2013). Earlier research conducted by Girmay, Singh, Nyssen and Borrosen (2009) estimated that soil loss ranged from 6 to 17.5 Mg ha^{-1} y^{-1} with soil and water conservation measures (SWC) and 15.5 to 56.7 Mg ha^{-1} y^{-1} without SWC measures on cultivated fields of the Ethiopian highland. The rate of soil erosion depend on erosivity (caused by external factors, such as climatic, landscape features and land use system) (Buttafuoco et al., 2012), and on the intrinsic properties of the soil's response to rainfall and runoff erosivity (Rousseva & Stefanova, 2006; Sanchis, Torri, Borselli & Poesen, 2008; Singh & Khera, 2008).

The soil's resistance to rainfall and runoff erosivity is therefore, considered as the inherent susceptibility of soil to be detached and translocated by erosion processes, such as splash erosion, surface runoff or both (Renard, Foster, Weesies, McCool & Yoder, 1997; Parysow, Wang, Gertner & Anderson, 2003) and can be dignified as soil erodibility factor (*K*-factor) (Parysow et al., 2003; Sanchis et al., 2008; Zhu et al., 2010). The concept of *K*-factor and how to quantify such parameter is complicated since the soil susceptibility to erosion is affected by a large number of physical, chemical, mechanical soil properties and hydrological processes (Bagarello, Di Stefano, Ferro, Giuseppe & Iovino, 2009). Several studies (Wischmeier, Johnson & Cross, 1971; Roose, 1977; Wischmeier & Smith, 1978; Laflen & Moldenhauer, 2003) describe *K*-factor as the rate of soil loss for unitary rainfall erosivity as measured on a unit plot. The unit plot is 22.18 m long, has a 9% slope, and is continuously maintained in a clean fallow condition with tillage performed upslope and downslope (Bagarello et al., 2009; Borselli, Cassi & Salvador Sanchis, 2009). Since *K*-factor is widely considered as a significant parameter in soil erosion/sediment process simulation models (Zhu et al., 2010), numerous attempt to simplify the *K*-factor evaluation procedure have been carried out in the past and simplified relationships have been proposed for predicting *K*-factor (Bagarello et al., 2009). According to Roose (1977) the USLE nomograph (Wischmeier et al., 1971) can be used to estimate *K*-factor of tropical soils predominated by ferrallitic and ferruginous soils, with the exception of soils that were gravelly or covered with rocky debris that acts as protective mulch.

Knowledge of the spatial patterns of *K*-factor is vital as it might guide us to prioritize and implement site-specific soil erosion control measures and during the past decade the spatial variability and correlation of *K*-factor at different landscape has been intensively studied and evaluated using both classical statistics and geostatistical methods (Wang, Gertner, Liu & Anderson, 2001; Veihe, 2002; Vaezi, Bahrami, Sadeghi & Mahdian, 2010; Buttafuoco et al., 2012;

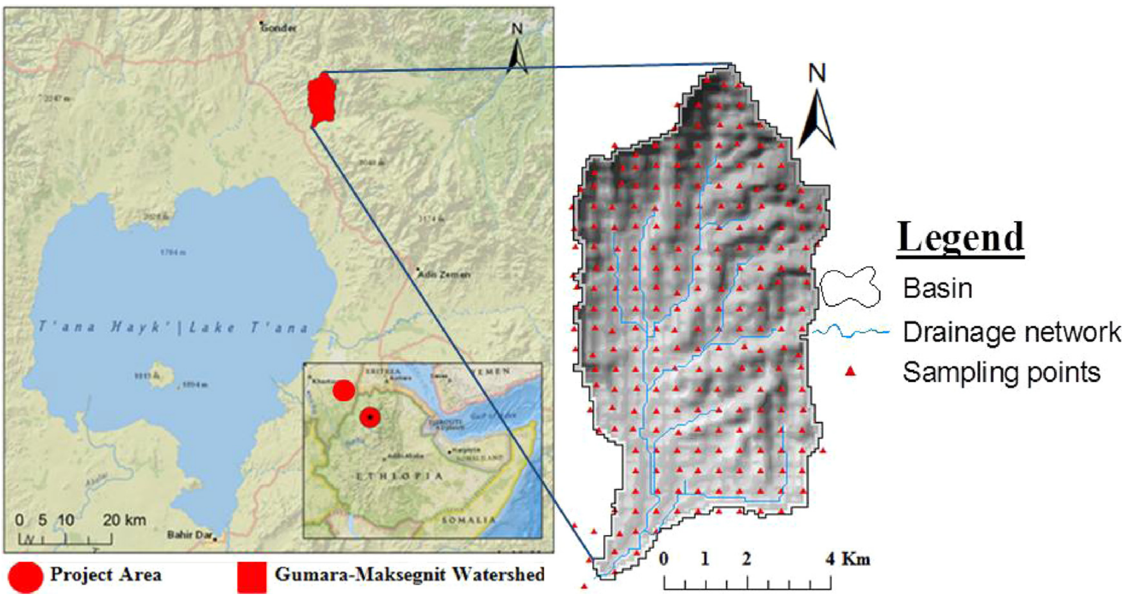

Fig. 1. Overview of the study watershed and distribution of the soil sampling locations.

Imani, Ghasemieh & Mirzavand, 2014). Geostatistics includes different methods that use Kriging algorithms for estimating spatially continuous variables (Li & Heap, 2008) and it can be used for assessing spatial variability of *K*-factor and have increasingly been utilized by soil scientists. Kriging is widely used for optimal estimation and spatial interpolation of values at unsampled locations (Li & Heap, 2008).

The enormous deforestation of native forest for crop production has largely contributed to the accelerated rainfall driven soil erosion and consequently to the wide agricultural productivity decline in the study watershed. Therefore, spatial continuous data of *K*-factor can be an important tool for implementing possible approaches for improving soil resistance in order to control erosion. At the moment, availability of information on the spatial variability of *K*-factors in the Ethiopian highlands at a watershed scale is scarce and variability of *K*-factor depends on the specific area examined however, such information for the study watershed is lacking. Therefore, the aims of this research were to estimate *K*-factor using the USLE nomograph, and assess the spatial variability of the predicted *K*-factor in a mountainous watershed.

2. Materials and methods

2.1. Descriptions of the study area

To investigate soil erodibility factor, a field survey was conducted in Gumara-Maksegnit watershed, located in the northwestern Amhara region, Ethiopia, between 12° 24’ and 12° 31’ North and between 37° 33’ and 37° 37’ East (Fig. 1) and this mountainous agricultural watershed has an area of 54 km^2 (Addis, Klik & Strohmeier, 2015). The main stream (Gumara-Maksegnit River) is a tributary of Lake Tana and originates in the north mountainous parts of the watershed at more than 2800 m above sea level (a.s.l). Gumara-Maksegnit watershed could be representative of wider sectors of the northern highlands of Ethiopia because of its geological, geomorphological and climatic features similarity. The climate of the watershed falls within Weyna Dega (cool sub-humid, 1500–2300 m) and Dega (cool to humid, 2300–3200 m), with average annual rainfall of 1170 mm and mean annual maximum and minimum daily temperature of 28.5 °C and 13.6 °C, respectively. The soil types are mainly Leptosol and Cambisol which are found in the central and upper part while, Vertisol is found around the outlet of the study watershed (Addis et al., 2015). Severe soil erosion, including sheet, rill and gully incision is widely occurred and it is the major environmental and social problem in the Gumara-Maksegnit watershed. The watershed was mainly covered by agricultural land (71%) followed by forest (25%), and grassland (4%), which were identified by means of supervised classification of spot satellite image (Addis et al., 2015).

2.2. Soil sampling procedures

The study watershed was divided into a 500 m by 500 m square grid and approximately, at the center of each grid, topsoil samples were collected over 234 locations within the study watershed (Fig. 1) (Addis et al., 2015). As a result of shallow depth in the study area, the topsoil depth was not fixed; instead roughly 10 to 20 cm depth ranges were applied. The soil sampling spots were selected using a well-organized regular sampling interval in a GIS environment, coupled with a careful selection of the most representative soil-landscape characteristics (terrine attributes, soil types, land use systems and the topsoil conditions) as it was described by Buttafuoco et al. (2012). Garmin explorer GPS accuracy: ($\pm$3 m) was used for locating the geographic coordinates of the sampling points in the field so that, topsoil samples of around 2 kg were removed with the best available tool (bucket auger) for analysis (Addis et al., 2015). During this study, sometimes the center of the square grid may not be a representative location, thus in such cases sampling point was shifted to the area which describe the grid well. The soil textures were analyzed following the procedure reported by Gee and Or (2002) while, soil organic carbon was determined by wet oxidation method as described by De Vos, Lettens, Muys, and Deckers (2007).

2.3. Soil erodibility factor (K-factor)

Soil erodibility factor is a complex concept and it is influenced by many soil properties, which can reflect the soil resistance to erosion (Buttafuoco et al., 2012). The most crucial soil variables that control *K*-factor include OM, clay content, bulk density, particle size distribution, shape, size and stability of aggregates, shear strength, porosity and permeability, and chemical composition (Duiker, Flanagan & Lal, 2001; Veihe, 2002; Sanchis et al., 2008; Morgan, 2009). The *K*-factor can be calculated via the Universal Soil Loss Equation (USLE), frequently applied to estimate soil erosion on the basis of other factors obtained from simulated or natural rainfall experimental data (Wischmeier & Smith, 1978). However, the direct estimation of *K*-factor is both expensive and time taking (Buttafuoco et al., 2012). In this study, the *K*-factors of the collected topsoil samples were estimated using USLE nomograph reported by Wischmeier et al. (1971), then modified by Foster, McCool, Renard, and Moldenhauer (1981) and Rosewell (1993), so as to definite the *K*-factor in international system of unit (SI unit) (Mg h MJ^{-1} mm^{-1}). The *K*-factor can be calculated from the observed soil values (texture, organic matter (OM), structural and permeability class) in accordance with Eq. (1):

$$K(\text{factor}) = 2.77 \times 10^{-7}(12 - \text{OM})M^{1.14} + 4.28 \times 10^{-3}(s-2) + 3.29 \times 10^{-3}(p-3) \tag{1}$$

where

$$M = [(100 - C)(L + Armf)] \tag{2}$$

C is % of clay (< 0.002 mm), L is % of silt (0.002–0.05 mm) and $Armf$ is % of very fine sand (0.05–0.1 mm) (Pérez-Rodríguez, Marques & Bienes, 2007), OM is the organic matter content (%), p is a code indicating the class of permeability, and s is a code for structure size, type and grade based on field observation and interpreted as described by Soil Survey Staff (1993). Then each soil texture is assigned a permeability class using (SSS, 1993) document.

2.4. Semivariograms

The *K*-factor is a quantitative description of a soil particles ability to resist moving downslope and this factor reflects the fact that different soils erode at different rates when the other factors that affect erosion are the same (Goldman, Jackson & Bursztynsky, 1986). This variability of *K*-factor across the study of interest can be described through a semivariogram model, which is a plot of the structure function that describes the degree of linear association between pairs of values separated by a given distance (Nielsen & Wendroth, 2003). In addition, semivariogram is useful for interpolation of values at unmeasured points across the study watershed (Li & Heap, 2008). Values of *K*-factor anywhere on the landscape differ from location to location, and spatial variations are generally highly irregular and not exactly described by deterministic equations, instead geostatistical analysis is used (Nielsen & Wendroth, 2003). In geostatistics, for N pairs of values of soil attribute A_i separated by a distance h, the semivariogram (a measure of the strength of statistical correlation as a function of distance) (Goovaerts, 1997) is calculated using equation (3):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [A_i(x_i) - A_i(x_i + h)]^2 \tag{3}$$

The software package GS+ (Gamma Design Software) version 10 (Robertson, 2008) was used to obtain the semivariogram model of *K*-factor, which were obtained through USLE nomograph. In this study, the semivariogram model with the least reduced sum of squares (RSS) was selected for spatial autocorrelation process as described by Addis et al. (2015). The RSS measures the overall difference between observed data and the estimated values by a prediction model and it is one of the best criterions for parameter and model selection. Meanwhile, the four commonly used semivariogram models reported by Burrough and McDonnell (1998) were tested to find the best

Table 1
Summary of descriptive statistics of the selected soil samples and the estimated K-factor in the study watershed.

Input parameters	Min	Max	Range	Mean	SD	SE (mean)	CV	Skewness
Clay (%)	11.6	67.8	56.16	29.29	13.33	0.87	0.45	1.07
Silt + very fine sand (%)	9.84	49.84	40.0	33.63	7.90	0.52	0.23	−0.94
OM (%)	0.21	8.0	7.79	2.66	1.73	0.11	0.65	0.84
Sand (%)	14.56	72.56	58.0	36.66	9.85	0.64	0.27	−0.18
K-factor (Mg h MJ^{-1} mm^{-1})	0.0	0.04	0.04	0.02	0.01	0.00	0.31	−0.26

OM = organic matter content. SD = standard deviation. SE (mean) = standard error of mean. CV = coefficient of variation.

fitted model. This study used cross-validation procedures, which removes one data point and then estimates the corresponding data using the data points at the rest of the locations and the main use of cross-validation is to compare the estimated value to the observed value in order to obtain useful information about variables (Davis, 1987; Li & Heap, 2008). The various cross-validation statistics are vital for examining how well the semivariogram model fits with the obtained data (Willmott, 1982). Some of the good criteria that the study used to decide the best model among the tested models were the mean error (ME), the root mean square error (RMSE) and the mean squared deviation ratio (MSDR).

3. Results and discussion

The measured soil properties, which were used to estimate soil erodibility, were subjected to descriptive statistical analysis. Summary of the classical statistics for the selected soil attributes observed in the watershed is displayed in Table 1. Over the sampled area, mean value of OM was $2.66 \pm 0.11\%$ while, mean value of observed soil texture (clay, silt and sand) were $29.29 \pm 0.87\%$, $33.63 \pm 0.52\%$, and $36.66 \pm 0.64\%$, respectively (Table 1). According to Borselli et al. (2009) Wischmeier's nomograph (Wischmeier et al., 1971) is not applicable for a silt content exceeding 70%, however, in the study watershed, the resulting silt content ranges from 9.84% to 49.84%, therefore, the USLE nomograph is applicable.

A soil variability can be defined through descriptive statistics and among the descriptive statistics, the coefficient of variation (CV) is the most significant parameter (Wei, Xiao, Zeng & Fu, 2008). When a CV is less than or equals to 0.15, the property shows low variability, moderate if CV is between 0.15 to 0.35 and most variable if CV is greater than 0.35 (Wilding, 1985). OM and clay content were the most variable soil properties, with CV greater than 0.35 while, silt and sand contents were moderately variable, with CV between 0.22 to 0.28 (Table 1).

The *K*-factor was calculated for all observed soil sampling points, except for some locations with OM content greater than 4%. The CV of *K*-factor was 0.31, suggesting a moderate variability in the study watershed (Table 1).

3.1. Spatial variability

The isotropic experimental semivariogram for the estimated *K*-factor was determined using Eq. (3). The semivariogram modeling and prediction is indispensable for spatial structural pattern analysis and interpolation (Burrough & McDonnell, 1998). The resulting spatial distribution of soil erodibility factor obtained using USLE nomograph was best fitted to the Gaussian model (Fig. 2) and the coefficient of determination (R^2) is equal to 0.904, which suggest that *K*-factor had stronger spatial structure (Table 2). The value of nugget to sill ratio (C_0/C_0+C) displays the spatial autocorrelation (Li & Reynolds, 1995). The soil erodibility factor had a nugget to sill ratio that ranges from 0.25 to 0.75, which categorized as moderate spatial autocorrelation (Cambardella et al., 1994), therefore surface map generation using ordinary Kriging method could be possible (Table 2). A small RSS indicates a model fits well with the obtained data and it represents unexplained variation (Draper & Smith, 1998). Therefore, based on the resulting RSS value in Table 2, the Gaussian model is selected as the best model for predicting *K*-factor.

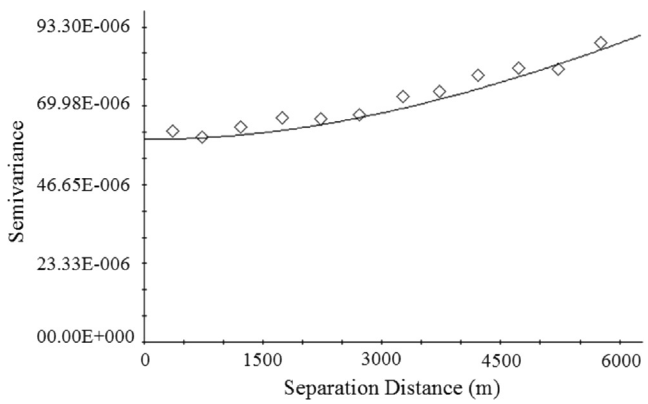

Fig. 2. The best fitted semivariogram model (the Gaussian model) of the estimated *K*-factor.

Table 2
Coefficients of the semivariogram statistic produced for the ordinary Kriging models of *K*-factor using Wischmeier's nomograph.

K-factor	Model types	Nugget (C_0)	Sill (C_0+C)	Range A_0 (m)	RSS	R^2	Nugget/sill
Wischmeier's nomograph	Spherical	0.00006	0.00013	20030	1.278E-10	0.865	0.46
	Exponential	0.00006	0.00018	21100	1.362E-10	0.856	0.33
	Linear	0.00006	0.00009	5706	3.490E-09	0.869	0.67
	Gaussian	**0.00006**	**0.00019**	**12060**	**9.020E-11**	**0.904**	**0.32**

RSS = residual sum squares. R^2 = coefficient of determination. Bolded RSS value was chosen as the best model.

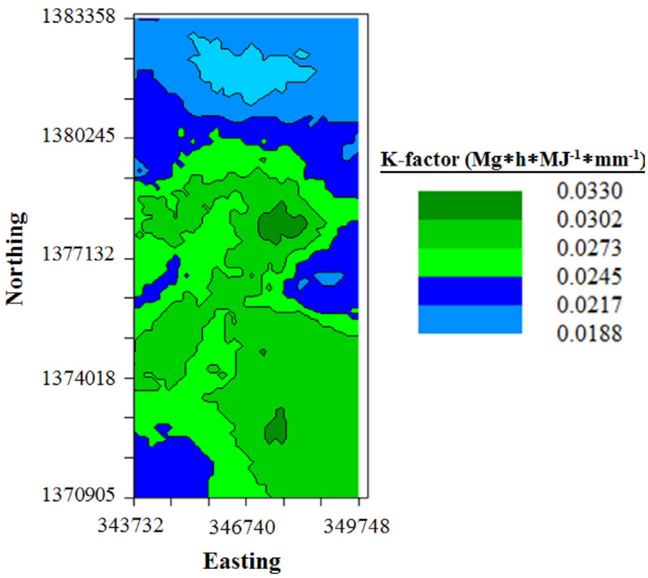

Fig. 3. Spatial distribution map of *K*-factor predicted by ordinary Kriging using the Gaussian semivariogram model.

Table 3
The cross-validation statistics, the mean error (ME), the root mean squared error (RMSE), and the mean squared deviation ratio (MSDR) for models listed in Table 2 fitted to the experimental semivariogram of *K*-factor.

Variable	Model types	ME	RMSE	MSDR
K-factor	Spherical	0.000	0.0089	1.05
	Exponential	0.000	0.0088	1.04
	Linear	0.000	0.0101	1.13
	Gaussian	**0.000**	**0.0086**	**0.99**

Bolded value was chosen as the best model.

3.2. Soil erodibility map

Spatial prediction map of *K*-factor created by ordinary Kriging interpolation procedure using the semivariogram coefficient of the Gaussian model in Table 2 is illustrated in Fig. 3. The inherent topographical variations and characteristics would be expected to influence organic matter content and soil particle transport, leading to spatial variability in *K*-factor which then influences soil erosion. The resulting values of *K*-factor (obtained using USLE nomograph) were small (0.0217 to 0.0188) in the north corner and gradually increased (0.0273 to 0.033 Mg h MJ^{-1} mm^{-1}) toward the central and south of the study watershed (Fig. 3). This could probably due to forest coverage in the northern parts of the study watershed that increases OM content, which ultimately lower *K*-factor (Tejada & Gonzalez, 2006). Meanwhile, intensive cultivation of agricultural lands with limited or no recycling of dung and crop residues in the central and southern parts of the study watershed lowers OM content which resulting in an increment of *K*-factor. The prediction of K-factor using the Gaussian ordinary Kriging model was relatively unbiased as the mean error (ME) was almost equals to 0 (Isaaks & Srivastava, 1989) while, the root mean square error (RMSE) was very low (0.0086), which indicates better model performance (Hu, Li, Lu & Zhang, 2004). The mean squared deviation ratio (MSDR) is most nearly 1 for the Gaussian model, which suggests the variance of measurement data is well reproduced with the ordinary Kriging interpolation method as it was described by Vašát, Pavlu, Boruvka, Drábek, and Nikodem (2013). In general, the cross-validation statistics is somewhat better for the Gaussian model of ordinary Kriging than exponential, spherical and linear function, but the differences were very small (Table 3).

4. Conclusions

Universal Soil Loss Equation (USLE) nomograph is essential method for *K*-factor calculation and this study successfully employed the USLE nomograph to estimate the spatial variation of *K*-factor at a watershed scale. The result indicates that the coefficient of variation of *K*-factor was 0.31, suggesting a moderate variability and the average estimated value of *K*-factor was 0.02. Meanwhile, the value of nugget to sill ratio of the estimated soil erodibility factor was between 0.25 and 0.75, which categorized as moderate spatial autocorrelation. The Gaussian function was the best semivariogram model to explain the spatial pattern of the estimated soil erodibility factor. The range of the spatial variation of soil erodibility factor was 12060 m and this lag distances was much longer than the sampling interval, thus the sampling design used in the study watershed for the estimated *K*-factor was adequately revealed spatial distribution. Generally, the predicted *K*-factor was relatively unbiased as the mean error was almost equals to 0 while, the root mean square error was very low, which indicates better model performance. Moreover, the mean squared deviation ratio (MSDR) is close to one, which indicates the variance of measurement data is well reproduced with the ordinary Kriging interpolation method. The estimated soil erodibility factor had the highest values at the outlet and central part of the watershed, while the lowest values of the soil erodibility factor was observed in the north and, rarely, in a small part in the other parts of the study watershed. The results of this study can be used to make recommendation of the *K*-factor in future soil erosion studies of data scarce similar regions of the Ethiopian highlands. Finally, the spatial pattern of the estimated *K*-factor accuracy and applicability of USLE nomograph for this watershed should be examined using direct measurement in standard plots under natural rainfall events, although direct estimation of K-factor is both expensive and time consuming.

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