Eco. Env. & Cons. 28 (February Suppl. Issue) : 2022; pp. (S242-S250)
Copyright@ EM International
ISSN 0971–765X

DOI No.: http://doi.org/10.53550/EEC.2022.v28i02s.040

Kriging Interpolation Based Error Analysis of Epic Model with Respect to Standard K Factor Method for Gurushikhar, Rajasthan, India

Narendra Kumar Maurya[1] and Prakash Singh Tanwar[2]* and Yusuf A.S.[3]

[1]Department of Civil Engineering, Madhav University, Pindwara, Sirohi, Rajasthan, India, [ORCID – 0000-0002-5003-3148]
[2]Department of CSE, Lovely Professional University, Phagwara, Jalandhar, Punjab, India, [ORCID – 0000-0002-2577-8682]
[3]Department of Civil Engineering, Madhav University, Pindwara, Sirohi, Rajasthan, India, [ORCID – 0-0000-0003-4114-955X]

(Received 13 June, 2021; Accepted 23July, 2021)

ABSTRACT

This paper investigates an error analysis of the K-factor by EPIC model and the Standard Table. Experiments accomplished to find various contents of soil and K-factor are calculated using the EPIC model and Standard Table is used for standard K values to consider them as true values. Kriging Interpolation is used to find unknown K-factors values in the Gurushikhar study area for both K-factor values. The prediction map for the K-factor is generated for the EPIC model, the Standard Table, and the Error of K-factor using the Kriging interpolation method. In the next section cross-validation comparison of the resulting maps is done. Results of high elevation regions show high negative errors and in plain regions, it shows positive errors. The regression function is generated using the collected and interpolated data. It also shows the high difference in multiplicative factor for "EPIC model K-factor" map and "K-Factor Error map" then "Standard Table K-factor map" and "Error map". Histograms for all sample points for Clay, Silt, Soil, and OMC are also created to understand the relationship with the most erroneous frequencies. The result shows that error is dependent on texture (Clay, Silt, and Soil) not on OMC in this study area.

Key words: *Kriging, Soil erosion, K-factor, EPIC Method, K-Factor Standard Table.*

Introduction

Soil erodibility (K factor) is a major issue in all factors of soil erosions. It affects the susceptibility of soil elements to detach and transport them by rainfall and runoff (Imani, *et al.,* 2014; Mazllom, *et al.,* 2016; Yang, *et al.,* 2018; Zhao *et al.*, 2018; Fu *et al.,* 2006; V., R., N. and H., 2011). Broadly, it has been used in practical and theoretical moves toward measuring soil erosion (Zhao, *et al.,* 2018). Soil erodibility is subjective by a lot of factors like soil properties (texture, configuration, organic substance content, and permeability), terrain, climate, vegetation, and land use (Yang, *et al.*, 2018). In past decades many strategies had developed to calculate soil erodibility. Such as mathematical models, instrumental measurement, measurements of physical and chemical soil properties, and graphical methods (Zhao *et al.,* 2018). However, the through measurements in large plot below natural rain-fall provides an accurate

[1]Research Scholar, [2]Associate Professor, [3]Associate Professor

opinion of soil erodibility. It is a lengthy and expensive method but it is a more accurate method (Imani *et al.,* 2014; Zhao *et al.,* 2018). They generally used mathematical models to estimate soil erodibility. There are some common erodibility estimation models such as the Nomogram Model (NOMO) (Wischmeier *et al.,* 1971), Modified Nomogram Model (M-NOMO)(Wischeier and Smith, 1978), Erosion-Productivity Impact Model (EPIC) (Williams, 1990), Torri model (Torri *et al.,* 1997), Shirazi model (Shirazi *et al.,* 1988), WEEP (Nearing *et al.,* 1989), Standard Table (Stone and Hilborn, 2012), etc.

The EPIC Model is (erosion-productivity impact calculator) a method for calculating the K factor using sand contented (%), silt contented (%), clay contented (%), and organic carbon contented (%) in the mathematical formula (Williams, 1990). Standard Table for the K factor was developed by Stone and Hilborn. In this method, a table is provided to determine the K issue from soil organic matters and texture investigation data (Stone and Hilborn, 2012).Interpolation is a method, which estimates values of unidentified points based on the importance of known points and constructs a spatial allotment map for the whole study region (Bhargava *et al.,* 2015; Bhargava, Bhargava *et al.,* 2016). Kriging method is a statistical interpolation method. It is used to globally interpolate the values using some known ethics in the learn area. Error investigation of K factor is calculated by getting the difference of K factor of EPIC model and standard table obtained from Kriging interpolation maps (Bhargava *et al.,* 2016).

In the past decades' various researchers reviewed the soil erodibility factor of soil erosion. They explained various existing soil erodibility methods and tried to find the best soil erodibility methods according to various aspects. Yang *et al*. reviewed soil erodibility that occurred due to water and wind erosion. They explained Soil erodibility as an important factor to assess soil erosion sensitivity. It is affected by several factors, for example, soil assets (organic matters contents, texture, formation, Permeability), human activities, etc. They calculated soil erodibility by various models, such as the NOMO model, WEQ and RWEQ model, WEEP and EPIC model, WEPS, and WESS model. The authors suggested the future scope for the upcoming research, to improve the measurement and calculation of soil erodibility to make the strong soil erodibility mechanism (Yang *et al.,* 2005).Zhao *et al*. reviewed possible techniques for opinion of soil erodibility and identify the simplest and easy method for the user and appreciate the influence factor of soil-erodibility. Here, they approximate the erodibility value with five methods, i.e. nomograph equations (NOMO), updated nomograph equations (U-NOMO), erosion-productivity impact model (EPIC), Shirazi model, and Torri model. The authors concluded that the Torri and Shirazi model are the simplest model intended for Ansai watershed. Soil erodibility estimation is directly linked to soil property and indirectly related to ecological factors (elevations, slope degree), vegetation cover, and human activities (Zhao, *et al*., 2018). Zhang *et al*. (2018) compared the SHIRAZI, NOMO, EPIC, and TORRI model for estimation of soil erodibility of Loess Plateau. The authors showed that the SHIRAZI model and erosion efficiency impact calculators (EPIC) model both are appropriate for the Loess Plateau (Zhang *et al.,* 2018).

NOMO Model is the simplest method to easily identify the values when we have more than two variables and the scale for these variables is available in Nomogram form. It is a graphical representation of variables in 2D form. Proper arrangement of scales is important in this method. Nomogram can be used to calculate the value without calculating it using formula. It is a graphical method that can be used by drawing lines along with the scales of various parameters. Drawing lines is easy for a layman and to find the value of the remaining variable. Due to its simplicity, various researchers worked on this method for a long time. Numerous authors worked on the NOMO model and M-NOMO for various study areas (Okorafor *et al.,* 2018; Imani *et al.,* 2014; Pereira, *et al.,* 2017; Addis and Klik, 2015; Belasri *et al.,* 2017).

Okorafor *et al*. (2018) showed that low to reasonable erodibility factor areas have low incidence of erosions, while the elevated erodibility factor area have an elevated tendency to attrition or have been eroded (Okorafor *et al.,* 2018). Imani *et al*. (2014) and Pereira *et al*. (2017) used kriging method for interpolation and constructed a spatial distribution map for the study area. Rasool Imani *et al*. concluded that the eastern area has low organic matter content and Eastern areas occur with high erodibility compare to the western areas of Iran. E.C.B. Pereira *et al*. (2017) concluded that the Curu valley tentative basin is exceptionally erodible by means of the Haplic Luvisol and Fluvic Neosol, the eutrophic Red-Yellow

Argisol is under the reasonably erodible class (Imani *et al.,* 2014; Pereira, *et al.,* 2017). Addis *et al*. used Gaussian semivariogram for interpolation and generated a spatial distribution map. They observed that the Gaussian semivariogram approach is best for accurate Prediction. Concluded that erodibility was smaller in northern-parts and frequently improved in the direction of the central and south of the study region (Addis and Klik, 2015). Belasri *et al*. (2017) utilized the GIS tool to generate the spatial allocation map of soil erodibility. They showed that the entire study area occurs in relatively moderate to severe soil erodibility. According to them clay particles are in the form of stable aggregates, so the clay particles resist detachment and reduce the potential of soil erodibility of the study region (Belasri *et al.,* 2017). Haidong *et al.* (2016) and Wang *et al*. utilized the EPIC model to analyse soil erodibility in the erosion estimation process (Haidong, *et al.,* 2016; Wang, Qian *et al.,* 2018; while, Esa *et al.* (2018) and Prasanna Kumar *et al.* (2011) used standard table for K factor (Esa *et al.,* 2018; V., R., N. and H. 2011).

Most of the researchers worked on various methods like NOMO, M-NOMO, EPIC, SHIRAZI, WEEP, and TORRI model, Standard table. Variation of error of K factor between EPIC model and the standard table is missing in all of the above work. Therefore, the objective of this paper is to cover a comparative study of the EPIC model with the standard table using Kriging interpolation and find suitability analysis of these two models.

Study Area

Gurushikhar is located in the southwest region of Rajasthan, (India). Its peak is the highest elevated place of the Aravali Range. The study area covers 122.35 km^2 and lies between 24.6°N and 24.7°N latitude & 72.74°E and 72.85°E longitude. It has a maximum elevation of 1,722 meters (5,650 ft) more than mean sea level. Its topography varies signiûcantly and altitude varied from 1722 m to 300 m above mean sea level. The climate is very humid with a minimum annual average rainfall of 376.5 mm and a maximum annual average rainfall of 3284.2 mm. Here, mostly rainfall occurs between July and September in the monsoon season. The minimum average temperature is approximately 19^{o}C and the maximum average temperature is approximately 35. The study area has clay loam and sandy clay loam type of soil. It is covered with a rocky mountain. Mostly granite rocks are available in the Gurushikhar region. The position of the learning area can be seen in Fig.1. It is mostly covered by forest and agricultural land.

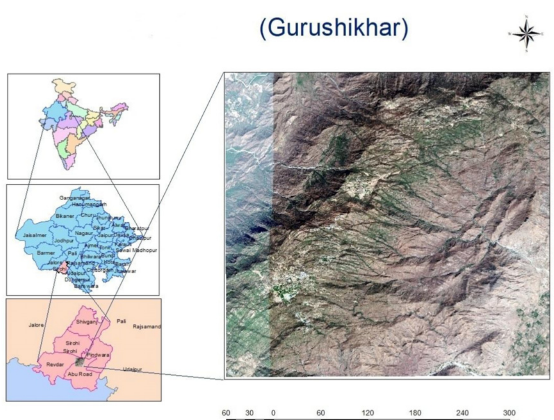

Fig. 1. Study area location map (Source: Google Earth Imagery)

Methodology

There are following methodology steps used in this study.

1. Surveying for sample collection.
2. Physicochemical Analysis to find OMC, OC, Texture (sand, silt, and clay) content in soil using bottle test with textural triangle method.
3. Organic carbon (%) is obtained by the Walkley - Black method.
4. Exchange Organic carbon (%) to Organic matters (%).

   % Organic Matters = Organic carbon (%) x 1.724 .. (1)

   Where, on average organic substance is collected by the stoichiometric percentage of 58% carbon, then 100/58= 1.724.
5. Calculate K Factor using standard Table [1].
6. Calculate K Factor using EPIC (Erosion-Productivity Impacts Calculators) Model.

$$K = \{0.2 + 0.3 \times e^{\left[-0.0256SAN\times\left(1-\frac{SIL}{100}\right)\right]}\} \times (SIL/(CLA+SIL))^{0.3} \left[1-\frac{0.25C}{C+e^{3.72-2.95c}}\right] \left[1-\frac{0.7SN1}{SN1+e^{22.9SN1-5.51}}\right] \quad ..(2)$$

Where, $SN1 = 1 - (\frac{SAN}{100})$

SAN = % of sand substance

SIL = % of silt substance

Table 1. K-factor resolute through soil organic substance and texture study data of Gurushikhar by means of Stone and Hilborn (2012) method

Textural Class	"K Factortons/hectare (tons/acre)"		
	Average OMC*	"Less than 2% OMC"	More than 2% OMC
Clay	0.490 (0.220)	0.540 (0.240)	0.470 (0.210)
Clay loam	0.670 (0.300)	0.740 (0.330)	0.630 (0.280)
Coarse sandy loam	0.160 (0.070)	–	0.160 (0.070)
Fine sand	0.180 (0.080)	0.200 (0.090)	0.130 (0.060)
Fine sandy loam	0.400 (0.180)	0.490 (0.220)	0.380 (0.170)
Heavy clay	0.380 (0.170)	0.430 (0.190)	0.340 (0.150)
Loam	0.670 (0.300)	0.760 (0.340)	0.580 (0.260)
Loamy fine sand	0.250 (0.110)	0.340 (0.150)	0.200 (0.090)
Loamy sand	0.090 (0.040)	0.110 (0.05)	0.090 (0.040)
Loamy very fine sand	0.870 (0.390)	0.990 (0.440)	0.560 (0.250)
Sand	0.040 (0.020)	0.070 (0.030)	0.020 (0.010)
Sandy clay loam	0.450 (0.200)	–	0.450 (0.200)
Sandy loam	0.290 (0.130)	0.310 (0.140)	0.270 (0.120)
Silt loam	0.850 (0.380)	0.920 (0.410)	0.830 (0.370)
Silty clay	0.580 (0.260)	0.610 (0.270)	0.580 (0.260)
Silty clay loam	0.720 (0.320)	0.790 (0.350)	0.670 (0.300)
Very fine sand	0.960 (0.430)	1.030 (0.460)	0.830 (0.370)
Very fine sandy loam	0.790 (0.350)	0.920 (0.410)	0.740 (0.330)

CLA = % of clay substance
C = % of organic carbon substance

7. Interpolate the remaining places for K factor for both methods
8. Calculate Error in K factor using EPIC Model with respect to Standard Table.
   Error = (K Factor using EPIC Model) - (K Factor of Standard Table value) (3)

Implementation

In the survey, 81 examples of surface soil (0-15 cm) were collected as of dissimilar places in the study area. The physicochemical analysis is determined in the soil science laboratory of Madhav University, Abu Road, Rajasthan for each soil sample. The particle size analysis was performed using the bottle test and textures are classified by the textural triangle method. Organic carbon was obtained as given in step 4 of methodology and then transformed to organic substance (%) by multiplying it by 1.724.

Here, the soil erodibility (K-factor) is determined by two methods, standard table, and EPIC Model. First, the standard table is used to establish the K-factor as of soil organic substance content and texture of the sample. Second, the EPIC model formula (Eq. (2)) is used to work out the K factor. At last, the error in EPIC method with respect to the standard table method of K factor is determined. ArcGIS is used to create a K factor map for both methods and an error prediction map using Kriging interpolation method.

Result and Discussion

According to soil sample data analysis, the study area has clay loam and sandy clay loam soil texture. Soil's feature table contains attributes Object_Id, Sample_No, Lat, Lon, Name_Location, Soil_Textural_Class, Clay, Silt, Sand, OMC, SN1, KEF1, KEF2, KEF3, KEF4, K_Factor_Standard_Table, EPIC_K_factor.

Where, SN1= 1 – (SAN/100),

$$KEF1= \{0.2 + 0.3 \times e^{\left[-0.0256SAN\times\left(1-\frac{SIL}{100}\right)\right]}\},$$

$$KEF2= (SIL/(CLA+SIL))^{0.3},$$

$$KEF3= \left[1-\frac{0.25C}{C + E^{3.72-2.95c}}\right]$$

$$KEF4= \left[1- \frac{0.7SN1}{SN1+e^{22.9SN1-5.51}}\right]$$

EPIC K factor is calculated in the Soil's feature table as shown in Fig. 2. EPIC K factor is calculated in the feature table using equation (2). According to Fig. 2, we can see that the K factor is in the range of 0.209884898 to 0.340330334 ton ac hr/(hundred-ft short-ton ac-inch) (with the precision of 9 decimal values). These values are calculated for only the sample points. Kriging interpolation is used to interpolate the values of unknown pixels of the study area. According to this map as shown in Fig. 2 we can conclude that most of the pixels are in the range 0.263 to 0.264.All of the figures shown here are created using ArcGIS, ESRI's GIS software.

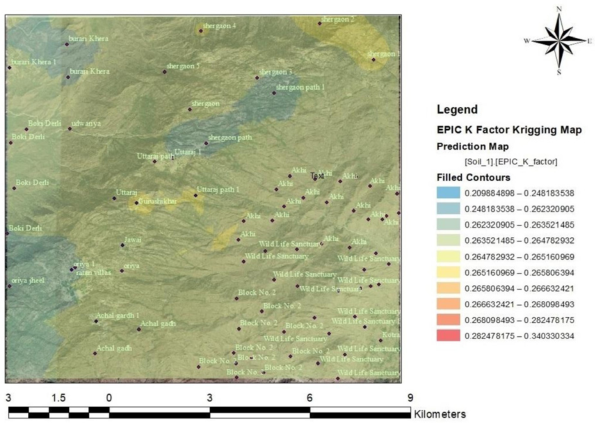

Fig. 2. Kriging Map of EPIC K factor

Fig. 3 shows that the Standard K table varies between .2 to .33. K factor for known points is taken from the sample points in the feature table. Kriging interpolation is used to interpolate the values of unknown pixels of the study area. According to this map as shown in Fig. 3 we can conclude that most of the pixels are in the range of 0.2 to 0.216 and 0.304 to 0.33.Error in EPIC K factor is calculated using the formula given equation (3). Here also the K factor for unknown pixels in the study area is calculated using Kriging interpolation. The resulting Kriging map of error is shown in Fig. 4. The map concludes that negative error increases in a hilly region and in plain area positive error. We can also observe high negative errors in the map up to -0.1 but the maximum positive error goes up to .069725267(0.067 approximately). If we compare the absolute error, then we can see that the maximum negative absolute value is .03 more than the positive absolute error. Here negative error shows that K factor of the standard table is more than K factor of EPIC model, it is shown in red shades in Fig. 4, similarly positive error shows that K factor of the standard table is less than K factor of EPIC model, it is shown in blue shades in Fig.4.

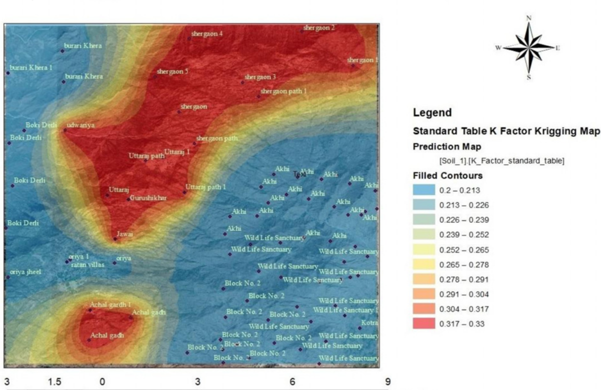

Fig. 3. Kriging Map according to Standard Table K fac tor

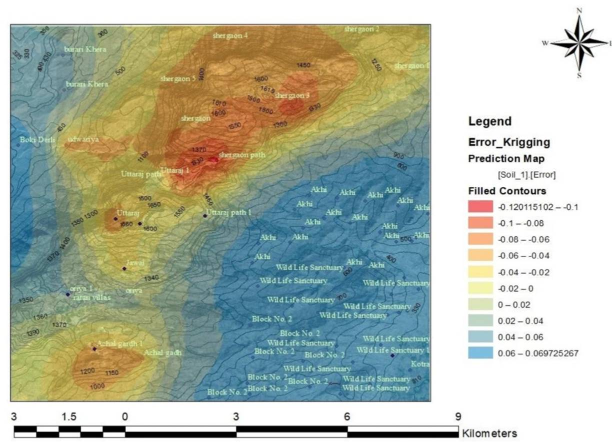

Fig. 4. Error estimation of EPIC K factor with respect to standard table K factor

Comparative Study

Table 2 is the comparative results of Error Kriging with K factor of Standard Table. The Study area has only two types of soils so only two values are selected in the feature map. The graph shown in Fig. 6 in the standardized error of standard Table K Factor, it can be observed that all known points K values have only two values, i.e. 2.0×10^{-1} and 3.3×10^{-1} (See x-axis values). The graph shown in Fig. 6 shows the standardized error of Error_Kriging Map, it can be observed that it is approximately similar to figure 5.

Table 3 is the comparative results of Error Kriging with EPIC model K factor. In the graph shown in Fig. 7 in the standardized error of EPIC Model K Factor, it can be observed that all known points K values have values in the range 2.09×10^{-1} and 3.4×10^{-1} (See x-axis values). The graph shown in Fig. 8 shows the standardized error of the Error_Kriging Map, it can be observed that it is not matched with the standardized Error_Kriging graph. Multiplicative constant of f3(x) is -37.005 (approx.) and f2(x) is -8.684 (approx.). There is a large difference between the multiplicative constant

Table 2. Cross Validation Comparison Standard Table K-factor Map with Error Kriging Map

	Standard Table K Factor Kriging Map	Error Kriging
Standardised Error	(Fig. 5)	(Fig. 6)

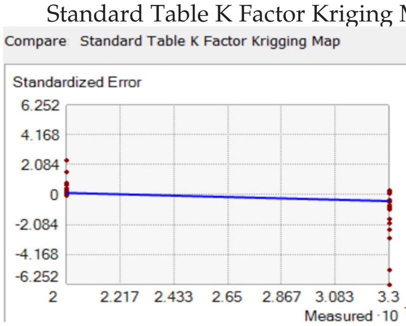

Fig. 5. Standardised Error Standard Table K Factor Kriging graph

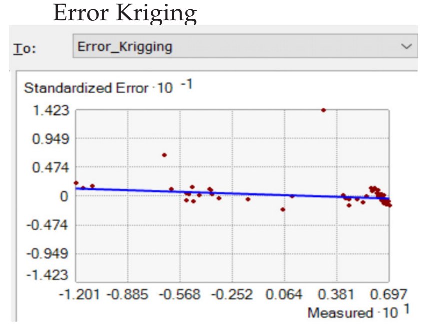

Fig. 6. Standardised Error and Error Kriging graph

Statistics

Regression function	-8.6846508732565 * x ...
Prediction Errors	
Samples	81 of 81
Mean	0.004580596
Root-Mean-Square	0.02976629
Mean Standardized	0.2244812
Root-Mean-Square Stan...	1.925451

Regression function	-8.6846508732565 * x ...
Prediction Errors	
Samples	81 of 81
Mean	0.004580596
Root-Mean-Square	0.02976629
Mean Standardized	0.2244812
Root-Mean-Square Stan...	1.925451

Regression Function	$f\,1\,(x) = -\,4.3811850278209\ x\ x + 1.00765402694018$	$f\,2\,(x) = -\,8.6846508732565\ x\ x + 0.2500705144480963$

Table 3. Cross Validation Comparison of EPIC K-factor Kriging Map with Error Kriging Map

	EPIC K Factor Kriging Map	Error Kriging
Standardised Error	(Fig. 7)	(Fig. 8)

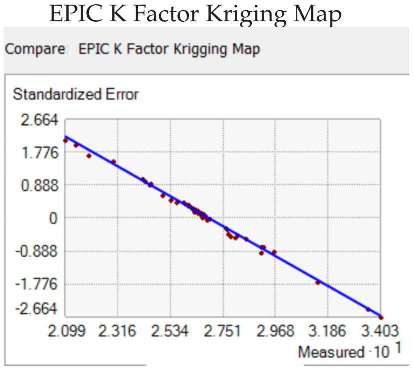

Fig. 7. Standardized Error of EPIC K factor Kriging Map Graph

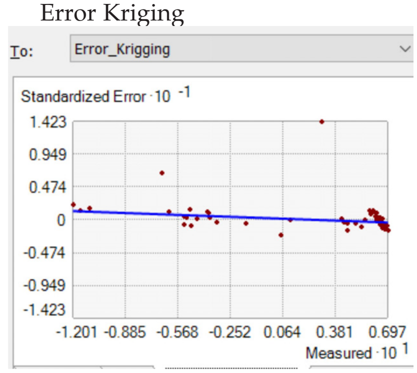

Fig. 8. Standard ized Error of Error_Kriging Map Graph

Statistics

Regression function	-37.0058935209244 * ...
Prediction Errors	
Samples	81 of 81
Mean	0.0028582
Root-Mean-Square	0.01923218
Mean Standardized	0.1112442
Root-Mean-Square Stan...	0.7069201

Regression function	-8.6846508732565 * x ...
Prediction Errors	
Samples	81 of 81
Mean	0.004580596
Root-Mean-Square	0.02976629
Mean Standardized	0.2244812
Root-Mean-Square Stan...	1.925451

Regression Function	$f\,3\,(x) = -\,37.0058935209244\ x\ x + 9.96860641929894$	$f\,2\,(x) = -\,8.6846508732565\ x\ x + 0.250070514480963$

Regression function for Standard Table K factor in the given study area is given as equation (4).

$$f\,1\,(x) = -\,4.3811850278209\ \ x\ x + 1.00765402694018 \quad (4)$$

Regression function for Error_Kriging in the given study area is given as equation (5).

$$f\,2\,(x) = -\,8.6846508732565\ x\ x + 0.250070514480963 \quad (5)$$

Regression function for EPIC Model in the given study area is given as equation (6).

$$f\,3\,(x) = -\,37.0058935209244\ x\ x + 9.96860641929894 \quad (6)$$

of both regression functions (as shown in the equation (5) and (6)).

After comparison of all maps, it concludes that for high precision the Standard Table K factor is not suitable for all regions. High negative error in the high elevation region concludes that the EPIC model K factor is more suitable in this region. Normal positive errors conclude that we can use any one of the models for the K factor in low elevation regions.

Out of 81 samples we have selected the sample points where most of the error occurs (Error frequencies go high) as shown in Fig. 9.

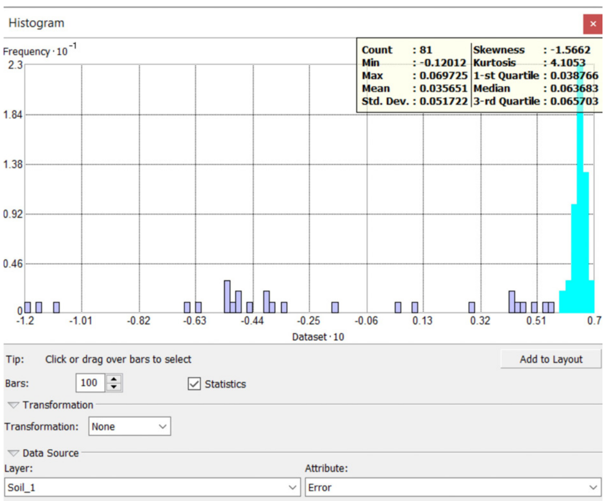

Fig. 9. Error Histogram (high frequency errors are highlighted)

Histograms for Clay, Silt, Sand, and OMC are also created to understand the relationship with the most erroneous frequencies. In Fig. 10, Fig. 11, Fig. 12, and Fig. 13 the highlighted sample points are the highest frequency points of Fig. 9.

Clay histogram of sample points is shown in Fig. 10. It shows that most high frequency erroneous sample points are grouped near clay=2.4. It shows that error depends on the clay part of the soil.

Silt histogram of sample points is shown in Fig. 11. It shows that most high frequency erroneous sample points are grouped in between 2.68 and 2.94. It shows that error depends on the silt part of the soil.

Sand histogram of sample points is shown in Fig. 12. It shows that most high frequency erroneous sample points are grouped in between 4.57 and 5. It shows that error depends on the sand part of the soil.

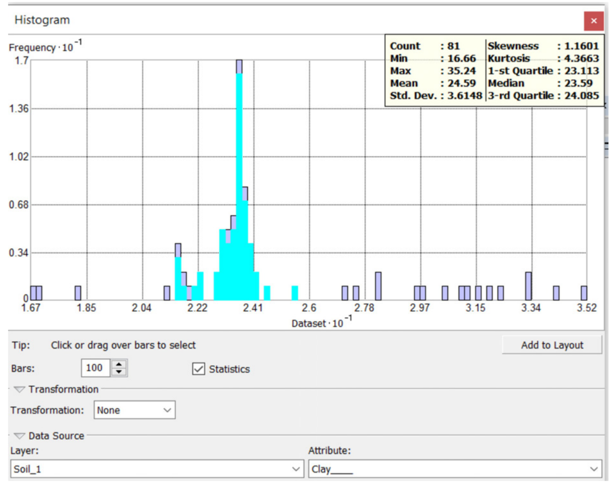

Fig. 10. Clay Histogram (high frequency errors are highlighted)

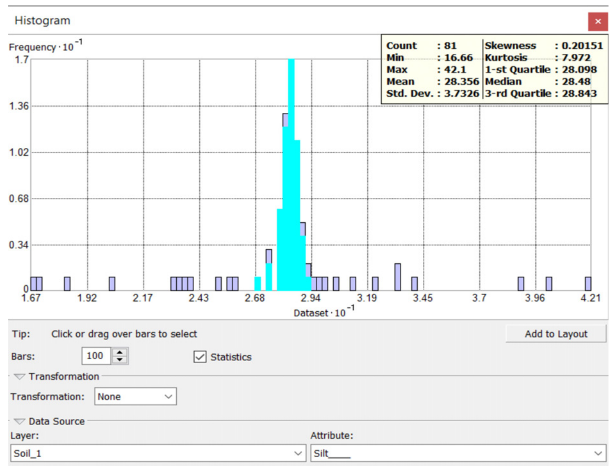

Fig. 11. Silt Histogram (high frequency errors are high lighted)

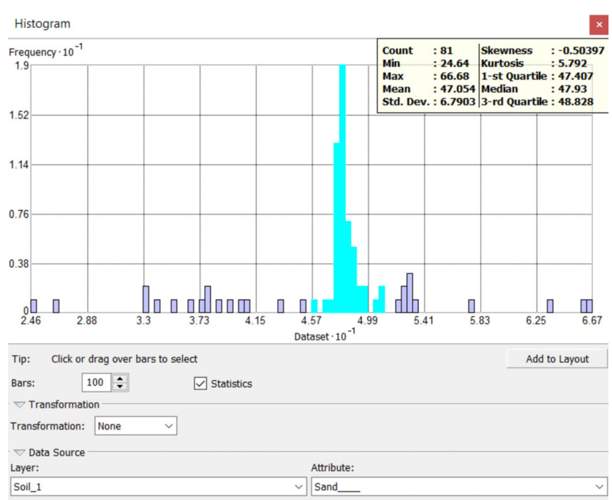

Fig. 12. Sand Histogram (high frequency errors are highlighted)

OMC histogram of sample points is shown in Fig. 13. It shows that most high frequency erroneous sample points are scattered. It shows that error does not depend on the OMC part.

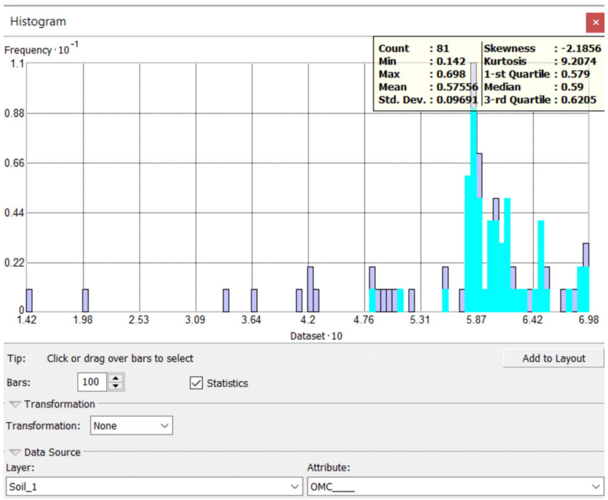

Fig. 13. OMC Histogram (high frequency errors are highlighted)

Finally, we can conclude that error in EPIC model K factor with respect to standard table k factor depends on the texture part of soil i.e. sand, silt and clay not on organic matter content.

Conclusion

Error analysis of K factor using the EPIC Model and Standard Table has been accomplished using kriging interpolation and histogram based statistical analysis.

Kriging Interpolation based error analysis concludes that high elevation regions show high negative errors from -0.120115102 to 0 and in the plain region, it shows positive errors from 0 to .069725267. Regression function shows the high difference in multiplicative factor for EPIC model K factor map and error map than Standard Table K factor map and error map.High negative error (-0.12 to 0) in the more elevated region (approx. 1200 to 1722 m) concludes that the EPIC model K factor is more suitable in this region. Normal positive error (0 to .069) conclude that we can use any one of the models for K factor in low elevation regions. Histogram based statistical analysis shows that error analysis of K factor using EPIC Model and Standard Table depends on texture content of the soil, not on organic matter content.These results are useful for researchers for a suitable method for K factor in the plain and hilly regions.

References

Addis, H. K. and Klik, A. 2015. Predicting the Spatial Distribution of Soil Erodibility Factor Using USLE Nomograph in an Agricultural watershed, Ethiopia. *International Soil and Water Conservation Research.* 3 : 282-290.

Belasri, A., Lakhouili, A. and Iben Halima, O. 2017. Soil Erodibility Mapping and its Correlation with Soil Properties of Oued El Makhazine watershed, Morocco. *Journal of Materials and Environmental Sciences.* 8 (9) : 3208-3215.

Bhargava, N., Bhargava, R. and Tanwar, P. S. 2015. Inherent Error Analysis of Slope Variable with IDW Method. *International Journal of Computer Science and Information Technologies.* 6 (4) : 3405-3409.

Bhargava, N., Bhargava, R., Tanwar, P. S. and Narooka, P. C. 2016. Comparative Study of Inverse Power of IDW Interpolation method in Inherent Error Analysis of Aspect Variable. *Information and Communication Technology for Sustainable Development.* Springer.2: 521-530.

Esa, E., Assen, M. and Legass, A. 2018. Implications of Land Use/Cover Dynamics on Soil Erosion Potential of Agricultural Watershed, Northwestern Highlands of Ethiopia. *Environmental Systems Research.* 7(21) : 1-14.

Fu, G., Chen, S. and Mccool, D. K. 2006. Modeling the Impact of No-Till Practice on Soil Erosion and Sediment Yield With RUSLE, SEDD, and Arc View GIS. *Soil & Tillage Research.* 85 : 38-49.

Haidong, G., Zhanbin, L., Lianlian, J., Peng, L., Guoce, X., Zongping, R. and Binhua, Z. 2016. Capacity of Soil Loss Control in The Loess Plateau Based on Soil Erosion Control Degree. *Journal of Geographical Sciences.* 26(4) : 457-472.

Imani, R., Ghasemieh, H. and Mirzavand, M. 2014. Determining and Mapping Soil Erodibility Factor (Case Study: Yamchi Watershed in Northwest of Iran). *Open Journal of Soil Science.* 4 : 168-173.

Mazllom, U., Emami, H. and Haghnia, G. H. 2016. Prediction the Soil Erodibility and Sediments load Using Soil Attributes. *Eurasian Journal of Soil Science.* 5 (3): 201-208.

Nearing, M. A., Foster, G. R., Lane, L. J. and Finkner, S. C. 1989. A Process-Based Soil Erosion Model for Usda-Water Erosion Prediction Project Technology. *Transactions of the ASAE.*32(5): 1587-1593.

Okorafor, O. O., Akinbile, C. O. and Adeyemo, A. J. 2018. Determination of Soils Erodibility Factor (K) for Selected Sites in Imo State, Nigeria. *Resources and Environment.* 8(1) : 6-13.

Pereira, E., L. F., Gomes, F., de Almeida, A., de Magalhães, A. and de Andrade, E. 2017. Determining the Soil Erodibility for an Experimental Basin in the Semi-Arid Region Using Geoprocessing. *American Journal of Plant Sciences.* 8 : 3174-3188.

Shirazi, M. A., Hart, J. W. and Boersma, L. 1988. A unifying quantitative analysis of soil texture: improvement of precision and extension of scale. *Soil Sci. Soc. of Am. J.* 52 : 181–190.

Stone, R. P. and Hilborn, D. 2012. *Universal Soil Loss Equation (USLE)*. (Queen's Printer For Ontario) Retrieved 9 8, 2020, from http://www.omafra.gov.on.ca: http://www.omafra.gov.on.ca/english/engineer/facts/12-051.htm

Torri, D., Poesen, J. and Borselli, L. 1997. Predictability and uncertainty of the soil erodibility factor using a global dataset. *Catena.* 31(1-2) : 1-22.

V., P., R., S., N., G. and H. V. 2011. Spatial Prediction of Soil Erosion Risk by Remote Sensing, GIS and RUSLE Approach: a Case Study of Siruvani River Watershed in Attapady Valley, Kerala, India. *Environ Earth Science.* 64 : 965-972.

Wang, L., Qian, J., Qi, W.Y., Li, S.S. and Chen, J. L. 2018. Changes in Soil Erosion and Sediment Transport Based on the RUSLE Model in Zhifanggou Watershed, China. *Proc. IAHS.*377: 9-18.

Williams, J.R. 1990. The Erosion-Productivity Impact Calculator (EPIC) Model: A Case History. *Phil. Trans. R. Soc. B.* 329 : 421-428.

Wischeier, W.H. and Smith, D.D. 1978. *Prediction Rainfall Erosion Losses: A Guide to Convervation Planning* (Vol. Agriculture Handbook No. 537). USDA Agriculture research service.

Wischmeier, W. H., Johnson, C.B. and Cross, B.V. 1971. A Soil Erodibility Nomograph For Farmland and Construction Sites. *Journal of Soil & Water Conservation.* 26(5) : 189-193.

Yang, S., Lianyou, L., Ping, Y. N. and Tong, C.O. 2005. A Review of Soil Erodibility in Water and Wind Erosion Research. *Journal of Geographical Sciences.* 15(2): 167-176.

Yang, X., Gray, J., Chapman, G., Zhu, Q., Tulau, M. and McInnes-Clarke, S. 2018. Digital Mapping of Soil Erodibility for Water Erosion in New South Wales, Australia. *Soil Research.* 56 : 158-170.

Zhang, X., Zhao, W., Wang, L., Liu, Y., Feng, Q., Fang, X. and Liu, Y. 2018. Distribution of Shrubland and Grassland Soil Erodibility on the Loess Plateau. *Int. J. Environ. Res. Public Health.* 15 (1193) : 1-17.

Zhao, W., Wei, H., Jia, L., Daryanto, Z. S., Zhang, X. and Liu, Y. 2018. Soil Erodibility and its Inûuencing Factors on The Loess Plateau of China : a case study in the Ansai watershed. *Solid Earth.* 9: 1507-1516.