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Original Article

Spatial Modeling of the K factor for two sub-catchments with different tillage and grazingCase study: loessial paired sub-catchments in the north-east of IRAN

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Abstract

Soil erosion is the most extensive process of land degradation worldwide that has negative impacts on sustainable development. In many hilly cultivated areas, erosion caused by tillage is at least as important as water induced soil erosion.In particular, the effect of tillage erosion on fertile loess soils is of high importance. We examined the effect of tillage on intensively cultivated and hilly loessial subcatchments in the north-east of the Golestan Province, Iran. In this study, different strategies to assess the soil erodibility factor in two sub-catchments with different management policies, which include tillage and grazing, are considered. Different interpolation approaches are compared using crossvalidation. For the first sub-catchment, all spatial modelling strategies forerodibility in terms of the K-equation result in the same mean value.However, this is not the case for the second sub-catchment. Tillage and grazing have a substantial effect on soil erodibility, but different strategies of implementing the K-equation may not give this result. Both sub-catchments have the same range of local uncertainty. We conclude that in case of mapping and assessing uncertainty, two different modelling strategies should be used.

Keywords: *Monte Carlo simulation, tillage erosion, soil erodibility, loess soils, Iran*

INTRODUCTION

Undoubtedly, soil erosion is the most extensive process of land degradation worldwide and in particular in semi-arid regions (Seager et al., 2007; Ravi et al., 2010). It causes great losses and these can have strong negative impacts on the sustainable development of the affected regions (Zhang, 1999). Some studies have shown that tillage erosion is at least as important as water erosion in many hilly and intensively cultivated areas (Lindstrom et al., 1992; Goverset al., 1994). Furthermore, loess soils are among the most fertile soils in the world (Catt, 2001) and about 10 % of the Earth's surface is covered with loess and loess-like (reworked loess) deposits (SPASSOV, 2002).Therefore, the effect of tillage erosion on such a fertile soil is of high importance. A soil's resistance to erosion can be measured by the K factor, the soil erodibility. It is generally considered as an indicator of an inherent soil property (Zhang et al., 2004) and widely adopted as an important factor in soil erosion prediction models.To improve the spatial prediction capability of erosion models, a continuous spatial function of input data is needed (Castrignanoet al., 2008). A kriged map is more suitable when global variability is of concern whereas a conditional simulation map is more suitable to describe local variability (Castrignano and Buttafuoco, 2004) and where the spatial variation of the measured field must be preserved (Srivastava, 1996).Conditional simulation is designed to overcome the smoothing effect of the kriging estimator (Deutsch and Journel, 1998). Thus, conditional simulation is especially advantageous when extreme spatial discontinuities have to be mapped. The knowledge of the estimation uncertainty at all locations and of all parameters is of great importance to reliably mark an area as "vulnerable" or "safe". Geostatistical stochastic simulation has the ability to predict the spatial distribution of the property more realistically than kriging andcanassess local and spatial uncertainty of the estimates.The knowledge of these associated uncertainties is helpful in decisionmaking (Goovaerts,1997; Deutsch and Journel, 1998). Furthermore, a simulation produces a set of realizations, also called a set of alternative equiprobable images, of the spatial distribution of the attribute as opposed to the single map of local best estimates obtained by kriging (Goovaerts,1997). This approach does not aim at minimizing local error variance, but focuses on reproducing statistics such as the sample histogram or the semivariogram model besides honouring data values (Goovaerts,1997; Deutsch and Journel, 1998). To assess the model output error resulting from the uncertainties in the input parameters, a Monte Carlo analysis (Paw and Orav, 1998) can be used. The model is then run for each single set of realizations of the input variables. We simulated all required variables for K, and the ensemble of model outputs to derive the output probability function. Nevertheless, many geostatisticians (Goovaerts, 2000) recommend that only simulations should be used to visualize maps because they offer the true representation of the stochastic component (i.e., the short-range variation) (Hengl and Toomanian, 2006).The most commonly used simulation technique for prediction and uncertainty assessment by constructing the conditional cumulative distribution function (ccdf) (Deutsch and Journel, 1998) is sequential Gaussian simulation (SGS) (Wang et al., 2002). Stochastic simulations became popular for spatial prediction and uncertainty assessment of soil properties in soil science in the recent decade(Pachepsky and Acock, 1998; Goovaerts, 2001; Juang et al., 2004; Delbariet al., 2009; Delbari et al., 2010).They are used for uncertainty assessment of the K factor estimation by Wang et al. (2001), Parysow et al. (2003) and Castrignanoet al. (2008). Although the spatial distribution of the K values has been widely studied, we are not aware of a case study like ours, where we follow different strategies to model K for loessial sub-catchments. It should be noted that both sub-catchments in this study are paired sub-catchments that have the same geology, topography and edaphic characteristics, but undergo a different management such as grazing and tillage. The objectives of this research were: (i) to prepare K maps using different strategies to model the K factor including: IC, CI, and MC and to compare them, (ii) to know their local and global uncertainties, and (iii) to compare the spatial changes resulting from erosion and tillage in these two hilly loessialsub-catchments. The paper is organized as follows. Section 2 provides materials and methods, and includesa brief description of the study area, soil sampling optimization, soil sampling and laboratory analysis. Thestatistical analysis, spatial stochastic simulation and the different strategies to model the K maps will be discussed. Section 3 deals with results and discussion whereas Section 4 contains concluding remarks.

MATERIALS AND METHODS

Description of the study area The area of interest is located in the north-east of Golestan Province, Iran.It is composed of two paired sub-catchments (Sample and Testifiersubcatchments; enclosed and open area, respectively) of a representative watershed (Fig.1). They include intensively exploited arable land with commonly cultivated crops such as sunflower, wheat, watermelon, artificial and natural forest. They are affected by diverse water erosions (sheet, rill, splash …) as well. The dominant soil texture in this area is clay, and soil depth varies from shallow to deep. The climate is typically semi-arid with an average annual temperature of about 16.7 °C and annual precipitation of 482 mm. The landscape is gently undulating with an average altitude of approximately 800 m. Figure 1 shows a map of the area of interest. Some characteristics of the area are given in Table 1 (values are partly taken from Hematzadehet al. (2009). Some protective activities in the sample sub-catchment include irrigation and conservation, planting seedlings and terracing by the office of Natural Resources and Watershed management of Golestan Province. In the Testifier sub-catchment only terracing (4 ha) was done by local people. Improved tillage, perpendicular to slopes, was conducted in the sample subcatchment as well.

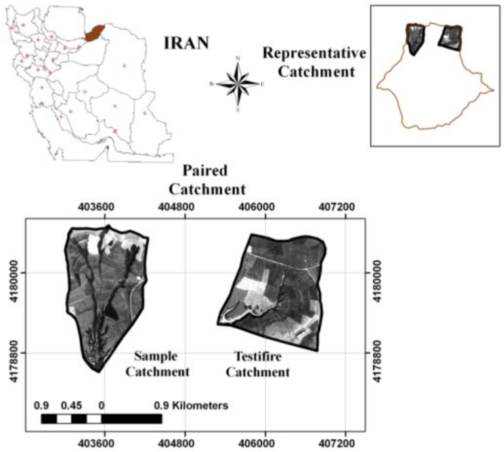


Fig.1: Map of study area

Table 1: Range of some characteristics of sub-catchments

Sub-catchments	Sample	Testifier
Mean Slope [%]	18.4	15.8
Elevation Range [m]	700-900	755-850
Area [ha]	191	196
Drainage Density [Km/Km^2]	1.62	2
Canopy Cover [%]	95	53
Grazing period	-	Jul- Oct
Enclosed time	1999	-

Soil sampling optimization

Since Gaussian simulation partly depends on the data configuration, in this study sampling optimization and spatial uncertainty are studied simultaneously. As widely known, sampling is constrained by different factors and an efficient one is sought. A great number of sampling strategies have been used so far. In this study, we used Latin Hypercube Sampling (LHS) alike several researchers in soil science (Pebesma and Heuvelink, 1999; Xu et al., 2005; Minasny and McBratney, 2006). However, we will not go into more details on LHS than that it is a stratified random procedure that provides an efficient way of sampling variables from a multivariate distribution. LHS provides a good coverage of feature space of the ancillary data. Since tillage erosion is also strongly affected by landscape structure, we used plan and profile curvatures (derived from a Digital Elevation Model, DEM) as ancillary data. Using a sequential-based method, the number of samples for each sub-catchment was determined to be 60. Soil sampling optimization was conducted by the lhs package (Carnell, 2009) and the statistical software environment R (R Development Core Team, 2011).

2.3. Soil sampling and laboratory analysis

According to sampling optimization and tillage depth, we collected topsoil samples (0 – 30 cm) across both sub-catchments using a steel auger in July 2010.

All physico-chemical soil attributes needed to derive soil erodibility (Equation 1) have been analysed in a soil lab. The soil erodibility factor by the nomograph expressed in SI units (t ha h ha^{-1} MJ^{-1} mm^{-1}) is given by

Eq.1

$$K = \frac{2.1 * 10^{-4}(12 - OM)M^{1.14} + 3.25(S - 2) + 2.5(P - 3)}{7.59 * 100},$$

where OM is the relative organic matter content , M is the product of the primary particle size fractions (Equation2), S is the soil structure code and P is the permeability class (Renard, Foster et al., 1997). M is defined as

Eq.2

$$M = (Si + VFS) * (100 - C),$$

where Si, VFS and C refer to silt, very fine sand and clay content of the soil in percentage respectively.

Statistical analysis

Descriptive statistics of the soil properties for each sub-catchment have been determined. The soil samples were tested to stem from a normal distribution using the Kolmogorov–Smirnov test as the stochastic simulation requires Gaussian distributed random variables. In case the test rejects the null hypothesis, the corresponding variable is transformed to a standard normal distribution by a normal score transformation.

Spatial stochastic simulation

Sequential Gaussian simulation (SGS)

The theoretical basis of geostatistics has been described by several authors (Journel and Huijbregts, 1978; Goovaerts, 1997). The main tool in geostatistics is the semivariogram that expresses the spatial dependence between neighbouring observations separated by a lag vector h. We obtained the experimental semivariogram and the fitted model by using the gstat R package (Pebesma, 2004).

In this paper, conditional SGS is used for spatial modelling and reproducing variability of silt, clay, very fine sand and organic matter for each sub-catchment. This technique aims at reproducing variogram and data distribution across N grid nodes. Furthermore, it is exact at sampling locations. Briefly, the study area is divided into N nodes on a grid, and the steps used for the SGS are given by (Goovaerts, 1997) as follows:

1. Define a random path visiting each node of the grid defined over the study area.
2. At the i-th node to be visited, model the conditional cumulative distribution function given the n original values and all (i -1) simulated values at the previously visited locations, using simple kriging with the modelled variogram.
3. For the i-th node, draw a realization from that conditional cumulative distribution function and this realization will become a conditional data for all subsequent drawings.
4. From the first node to be visited, repeat steps 2 and 3 above until all N nodes are visited and each has received a simulated value.

A variogram model was produced for all variables of interest. All analyses were carried out on 1000 The study was conducted in 13 forest stands in Bani and Sarthal areas of district Kathua of Jammu Shiwaliks (32° 36' 38" N to 32° 41' 00" N latitude and 75° 48' 38" to 75° 48' 38" E longitude) covering an area of 381 km² (Fig 1). The tract can be altitudinally divisible into subtropical (580m asl to 1500 m asl), temperate (1500 m asl to 3500 m asl) and alpine (>3500 m asl) zones as reported by Saxena et al. 1985. Mean annual maximum temperature range from 34.5 $\pm$

realizations of a two-dimensional field grid for each sub-catchment. After all N nodes were visited and all the simulated data was obtained, transformed variables were back transformed into the original scale.

Sequential indicator simulation (SIS)

The SIS relies on indicator kriging to infer the ccdfs. We used the SIS to interpolate the permeability classes (Renard et al., 1997). The simulated realizations numerically approximate the ccdf for every single location. Post-processing allows us to obtain different measures of predicting quality and uncertainty. A corresponding conditional variance map, which represents the spread of estimated ccdfs, can also be produced. All simulations were done using the R package gstat (Pebesma, 2004). The geostatistical simulations are used as input for the K model (see equation 1).

Different strategies to model the K maps

MC and uncertainty analysis

Uncertainty of soil erodibility will be determined using the simulated variables for each sub-catchment obtained from the Monte Carlo simulation (MC). The assessment of the uncertainties in the model predictions is based on 1000 realizations. The spatial uncertainty is defined as the uncertainty prevailing jointly at several locations (Goovaerts, 1997) and it can be used to assess the reliability of delineating (based on the single-location uncertainty measure) vulnerable areas as well. Spatial variation of K refers to its deterministic variation for a single realization of input variables, whereas uncertainty refers to the distribution of K for a single point obtained from the ensemble of MC simulations.

IC and CI

The method denoted with IC refers to kriging of all input variables of K first followed by the calculation of K. The reverse order is referred to by CI where K is computed at every sample location and a map is prepared by kriging afterwards.

4.30 ^{0}C, whereas mean annual minimum temperature is recorded as 6.35 $\pm$ 2.50 ^{0}C. Average annual rainfall ranges from 1450 mm at moderate altitudes (< 2000 m) and gradually declines to 800 mm beyond 2500 m. The study area is characterized by four major seasons: short spring (February - March); warm and dry summer (mid April to mid July); warm and wet *monsoon* (mid July to mid September) and relatively dry winter (mid-October to February).

Sampling procedures and Data analysis:

After the reconnaissance survey, thirteen forest types interspersed in different climatic and physiographic regimes have been identified and recorded. The forest types have been classified as per Champion and Seth (1968) and named according to the composition of dominant trees species as per Ram Prakash (1986), *viz.,* ≥ 75 % as pure; 50 - 75% as mainly; 25-50% as mixed and < 25 miscellaneous. Physiographic factors like altitude and slope aspects across different cover types were measured by GPS. A total of 750 plots each measuring 20 x 20 m were laid for quantitive analysis of tree vegetation. Plots were laid by stratified random analysis with the objective to include at least 0.01 % of the total area and the quadrat area was determined by using species area curve.

Trees were considered to be individuals > 10 cm dbh (Knight, 1963). Total species richness was simply taken as a count of number of species present in the respective forest type. Species richness (number of species per unit area) was calculated as Margalef's Index (1968) using formula SR = S-1/ln (N) and Menhinik's index of richness (Whittaker, 1977) was calculated as Richness = S/√N, where, S = number of species and N = Total number of individuals (of all species in case of Menhinik's index). The diversity (H') was determined by using Shannon-Weiner information index (Shanon and Weaver 1963) as H'= - ∑ni/n log2 ni/n ; where ni was the IVI value of a species and n was the sum total IVI values of all species in that forest type. Simpson's diversity index (Simpson, 1949) was calculated as D: I-Cd, Where Cd = Simpson's concentration of dominance = $(\sum ni/n)^2$.

RESULTS AND DISCUSSION

Descriptive statistics of the variables are given in Table2. We applied a normal-score transformation to Clay in the sample sub-catchment. Some statistical characteristics of the three different approaches to model K are presented in Table 3

.**Table 2**: Descriptive statistics of variables of interest

sub-catchments	variable	Mean	Max	Min	SD	Skewness	Kurtosis	CV
Sample	Very fine sand	3.6383	7	1	1.5125	0.4859	-0.4367	0.4157
	Silt	14.5333	29.2	1.2	5.3825	0.0116	0.2401	0.3703
	Clay	56.2333	68.8	8.8	14.5117	-1.8051	2.5925	0.2581
	Organic matter	2.6722	4.0952	1.6032	0.6034	0.2241	-0.5487	0.2258
	Permeability class	-	6	2	-	-	-	-
Testifier	Very fine sand	2.665	5.5	1	0.8837	0.3836	0.5747	0.3316
	Silt	18.1767	27.2	9.2	4.3807	0.2237	-0.6123	0.2410
	Clay	49.89	78.8	8.8	17.8372	-0.8653	-0.2823	0.3575
	Organic matter	2.1292	3.4546	0.4159	0.6955	-0.2538	-0.6322	0.3266
	Permeability Class	-	6	2	-	-	-	-

We applied a normal-score transformation to Clay in the sample sub-catchment. Some statistical characteristics of the three different approaches to model K are presented in Table 3.

Table 3: Descriptive statistics of different strategies of K

Sub-catchments	strategies	Min	1st quantile	Median	Mean	3rd quartile	Max	Range	Simulation size
Sample	IC	0.0043	0.0098	0.0102	0.0102	0.0105	0.0121	0.0078	-
	CI	0.0095	0.0098	0.0099	0.0099	0.0099	0.0101	0.0061	-
	MC	0.0057	0.0093	0.0097	0.0097	0.0104	0.0114	0.0057	1000

Testifier	IC	0.0081	0.0118	0.0129	0.0129	0.0140	0.0183	0.0102	-
	CI	0.0040	0.0078	0.0094	0.0091	0.0104	0.0149	0.0109	-
	MC	0.0043	0.0076	0.0085	0.0085	0.0094	0.0123	0.0078	1000

Box plots of all different approaches are illustrated in Figure 2.

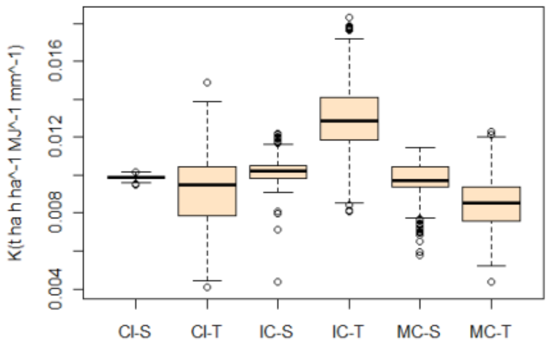
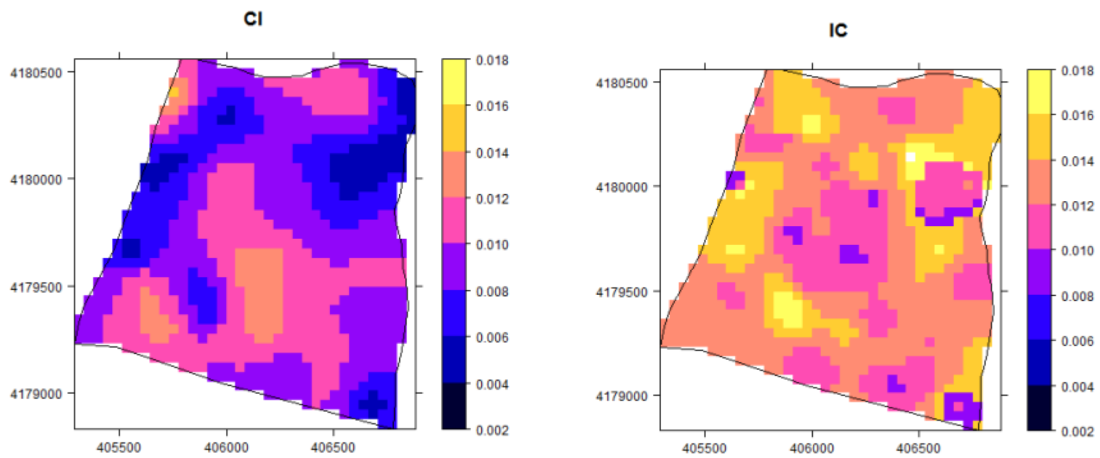


Fig.2: Box-plots for different strategies of K. S: Sample, T: Testifier

K factor maps for both areas with different modelling strategies are shown in Figures 3 and 4. In case of the sample sub-catchment, the CI strategy follows a pure nugget effect and its map is omitted. The map of the MC approach is derived as the mean of all 1000 realizations per grid cell.



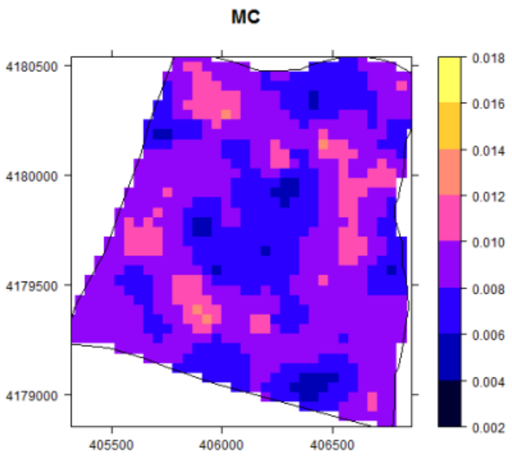


Fig.3: Maps of the K factor with IC and MC strategy for Testifier sub-catchment

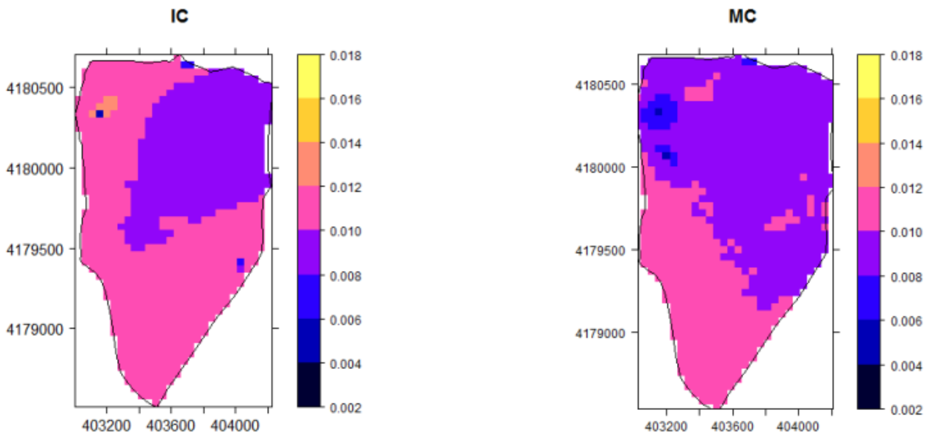


Fig.4: Maps of the K factor with different strategies for testifier sub-catchment

Histograms of the highest and lowest local uncertainty for K are depicted in Figure 5. The global uncertainty for K is illustrated in Figure 6. Range and mean of theK factor are illustratedas vertical lines as well. The minima for both subcatchments are the same.Histograms of the highest and lowest local uncertainty for K are depicted in Figure 5.

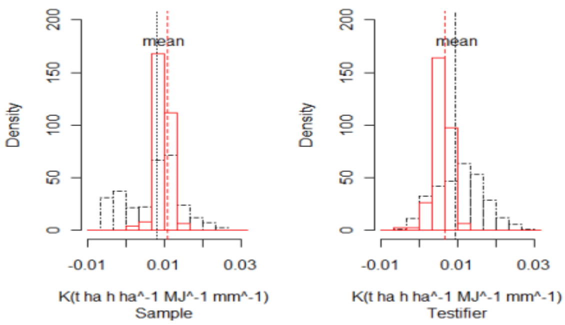


Fig.5: The highest (dashed histogram) and the lowest local uncertainty for K for both sub-catchments

The global uncertainty for K is illustrated in Figure 6. Range and mean of the K factor are illustrated as vertical lines as well. The minima for both sub-catchments are the same.

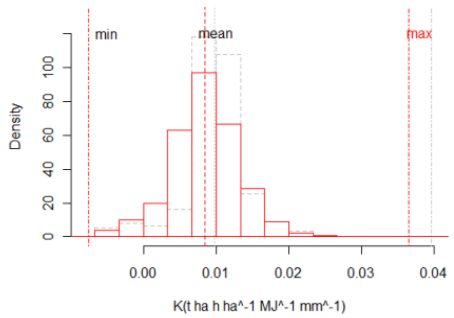


Fig.6: Global uncertainty for K. Dashed histogram: Sample sub-catchments.

Since we studied local and global uncertainties in this paper by MC simulation, some simulation maps for K are presented in Figure 7.

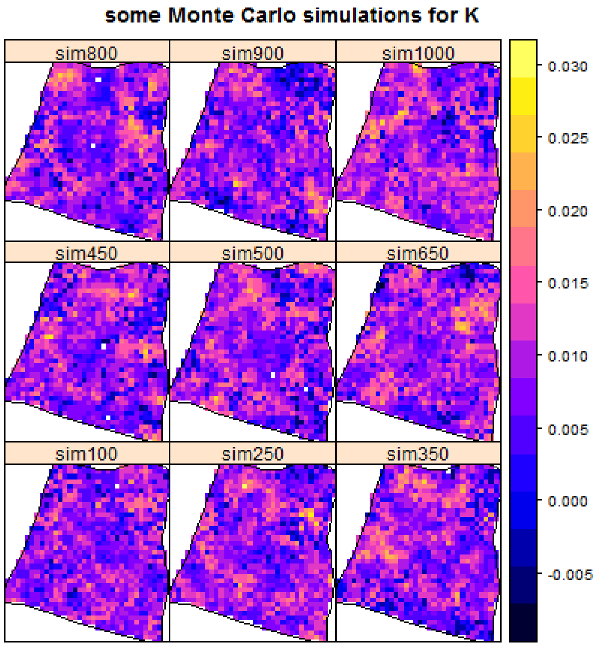


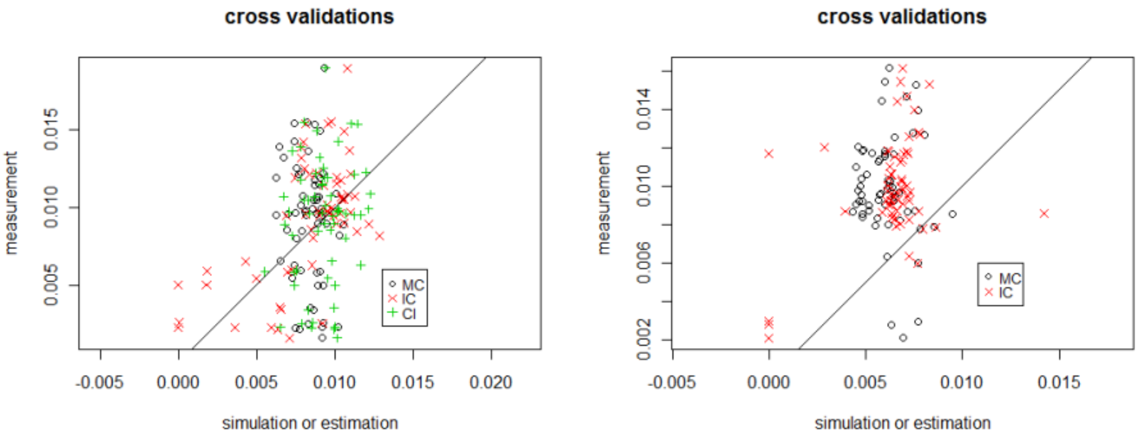
Fig.7: Maps of some simulations of K for Testifier sub-catchment

Cross validation for different strategies in this study are given in Table 4 and are illustrated in Figure 8 as well.

Table 4: Some criteria of cross validation for different strategies

	strategies	RMSE	RSQR	Bias
Sample	IC	0.0048	0.1709	-0.0030

	CI	0.0028	0.2691	0.0007
	MC	0.0049	0.0069	-0.0031
Testifier	IC	0.0033	0.3599	-0.0009
	CI	0.0039	0.0277	0.0000
	MC	0.0042	0.0174	-0.0008



A). Testifier sub-catchment B). Sample sub-catchment

Fig. 8: Cross validation for different strategies

CONCLUSION

A great number of suitable tillage models have been applied so far. We considered three different approaches to spatially model the K factor. Focussing on a simple and widely used formula for the K factor (Eq. 1), we studied the different outputs of the investigated approaches. For the two sub-catchments, they showed to some extent different results. Since K depends on the differences in ecosystem functions over a research area, any equation of estimating it should have dynamic and interactive variables to account for changing land properties.

For the Sample sub-catchment, all strategies for spatial modelling of the K equation result in the same mean. With regards to cross validation results, the best strategy is CI. However, it has completely different results from the others. Since this approach models a pure nugget effect, it shows no spatial dependency of soil erodibility. Thus, we used the second best model. IC and MC, in this case, are nearly the same and show fairly the same results. Generally, spatial structures for IC and MC are nearly the same, but MC shows much more local spatial variability.

For the Testifier sub-catchment, all strategies for the spatial modelling of the K equation result in different means. As Rejman (1998) showed, soils developed from loess are highly spatially differentiated over short distances. We see many changes and different strategies to evaluate the K equation show various outputs. With regard to cross validation, IC is the best. The spatial structure of IC and MC are nearly the same, but the CI method is very smooth and completely different.

Comparing two sub-catchments over the short period from 1999 to 2010, there is a decrease in the soil erodibility factor in the sample sub-catchment. This factor is affected by tillage and grazing management. Therefore, we can strongly say that tillage and grazing have a substantial effect on the increase of soil erodibility, but different strategies of implementing the K equation may not give this result. In this case, some novel techniques based on for instance on the radionuclide Be-7 should be employed. They show short term changes resulting from tillage, grazing and land use changes. This technique has its merits and limitations as well. Using some methods like common one in this study is full of uncertainty, different strategies, and not precise results. Therefore, apart from model precision, its simplicity is very important to get the same results with different implementations.

In case of local uncertainty, both areas have the same range of local uncertainty. In contrast to the testifier sub-catchment, the mean of highest uncertainty is less than the mean of the lowest uncertainty the sample sub-catchment. It means that most of the highest uncertainty covers negative values of soil erodibility. However, these are in reality impossible and are a consequence of adopting a Gaussian distribution. The grid cell with the highest local uncertainty, in the Testifier sub-catchment, is related to K values more than K mean for pixel of interest. It may be because of human effects on soil erodibility that is full of uncertainty which needs more cautious decision making. In case of global uncertainty, Sample sub-catchment has the higher uncertainty than that in Testifier sub-catchment that may be because of some management practices that have employed there.

With regards to Figures 3 and 4, this study shows that kriging maps are partly smoother than simulated ones using MC. Theoretically, MC provides a more realistic local variability and assessment of the uncertainty. However, the cross validation shows, IC is slightly better than MC. We conclude that in case of preparing map and assessing uncertainty, both modelling strategies should be used.

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