Improved calibration of Green-Ampt infiltration module in the EROSION-2D/3D model using a rainfall-runoff experiment database

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Abstract. Soil infiltration is one of the key factors that has an influence on soil erosion caused by rainfall. Therefore, a well-represented infiltration process is a necessary precondition for successful soil erosion modelling. Complex natural conditions do not allow the full mathematical description of the infiltration process and additional calibration parameters are required. The Green-Ampt based infiltration module in the EROSION-2D/3D model introduces a calibration parameter skinfactor to adjust saturated hydraulic conductivity. Previous studies provide skinfactor values for several combinations of soil and vegetation conditions. However, their accuracies are questionable and estimating the skinfactors for other than the measured conditions yields significant uncertainties in the model results. This study brings together an extensive database of rainfall simulation experiments, the state-of-the-art model parametrisation method and linear mixed effect models to statistically analyse relationshis between soil and vegetation conditions and the model calibration parameter skinfactor. New empirically based transfer functions for skinfactor estimation significantly improving the accuracy of the infiltration module and thus the overall EROSION-2D/3D model performance are provided in this study. Soil moisture and bulk density were identified as the most significant predictors explaining 82% of the skinfactor variability, followed by the soil texture, vegetation cover and the impact of previous rainfall events. The median absolute percentage error of the skinfactor prediction was improved from 71% using the currently available method, to 30-34% using the presented transfer functions, which lead to significant decrease of error propagation into the model results compare to the present method. The strong logarithmic relationship observed between the calibration parameter and soil moisture however indicates high overestimation of inifltration for dry soils by the algorithms implemented in EROSION-2D/3D and puts the state-of-the-art parametrisation method under question. An alternative parameter optimisation method including calibration of two Green-Ampt parameters saturated hydraulic conductivity and water potential at the wetting front was tested and compared with the state-of-the-art mehod, which paves a new direction of future EROSION-2D/3D model parametrisation.

1 Introduction

Soil erosion modelling is a common and efficient approach to analyse and understand the soil erosion process and propose solutions to minimize its impact. Therefore, development and improvement of soil erosion modelling tools are of crucial interest among soil scientists, state land offices, or landscape architects. EROSION-2D and EROSION-3D are soil erosion modelling tools based on the same physical descriptions of soil erosion processes on hillslopes (2D) or in catchment areas (3D) for single rainfall events. In this paper EROSION-2D/3D shall refer to both versions, where shared algorithms are discussed. These tools are able to predict erosion patterns, as well as deposition areas, on agricultural fields, infrastructure, and settlement areas (von Werner, 2007). The physical based algorithms allow to apply EROSION-2D/3D under various circumstances, from long term simulations, covering catchments of several square kilometres (Routschek et al., 2014), to short term reconstructive simulations of small catchments (Hänsel et al., 2019).

EROSION-2D/3D includes two submodules. The first submodule is an infiltration module used to calculate infiltration rates over time. The second submodule uses the infiltration rates to calculate excess water, surface runoff, and detachment, as well as the transport and deposition of particles. The infiltration submodule is based on the Green-Ampt approach (Schmidt, 1996). This approach assumes a rigid, homogeneous, and permanent submerged soil column. Such conditions are rarely met in nature and the model parameters usually require calibration to compensate this simplification. The infiltration submodule in EROSION-2D/3D requires input parameters that can be measured or predicted with common methods (i.e., bulk density, initial soil moisture, grain size distribution, and organic bound carbon) and the skinfactor calibration parameter, which scales saturated hydraulic conductivity. The skinfactor can be determined from rainfall-runoff experiments with the hillslope simulation tool EROSION-2D (Michael et al., 1996). As EROSION-2D can only be parameterized manually in a graphical user interface this process required extended time to iteratively change skinfactor values, limiting the skinfactor determination to a relatively small number of combinations of soil and vegetation conditions.

Previous studies have focused on estimating skinfactors for those other than measured conditions. The studies are based on 116 rainfall experiments conducted in Saxony (Germany) between 1992 and 1995, which are published in the EROSION-3D Catalogue of Input Parameters (Parameter Catalogue) (Michael et al., 1996). Michael et al. (1996) and von Werner (2009) estimated the skinfactors using information on German KA5 soil textural classes (Sponagel and Ad-hoc-Arbeitsgruppe Boden, 2005), initial soil saturation (dry or wet conditions), plant development stages, management practices, and field conditions. All of the predictors were categorical variables. The resulting matrix of skinfactor values provides guidance for a limited number of vegetation and soil condition combinations, which is available in the Parameter Catalogue for model users. However, the statistical background of the matrix and the selection of the predictors were not published and are not traceable. For other conditions, users must estimate values by themselves from the limited and incomplete matrix. Another approach (Michael, 2000; Schlegel, 2012) was to predict skinfactors from the numeric soil input parameters of the infiltration module (i.e., clay, silt, sand, organic carbon, bulk density, and soil moisture). Both studies used regression models to analyse the strongest predictors for different groups of experiments according to the soil types, management practices, and moisture conditions. The entire dataset shows the strongest correlation between the skinfactor and the bulk density, soil moisture, and silt content, but with a

55 low statistical significance and small correlation coefficient. Analysis of specific groups of experiments (e.g., sandy soils and conservational management practices) exhibits better results, but are based on an insufficient number of experiments.

For this study, an R package toolbox.e3d was developed to enable automatic and batch determination of the skinfactors for multiple rainfall-runoff infiltration experiments. An extensive rainfall-runoff experiment database was processed by the package, creating a sufficient amount of data to statistically analyze the relationships between the skinfactor and other param-

60 eters describing the soil and vegetation conditions of the experiments. The aim of this study is to improve the performance of EROSION-2D/3D by providing easy to use transfer functions to calibrate the infiltration module of the model.

2   Data and methods

2.1   Infiltration module

The infiltration model used in EROSION-2D/3D was developed by Schmidt (1996) based on the Green-Ampt infiltration

65 approach (Green and Ampt, 1911). The following equations are all quoted from Schmidt (1996) unless otherwise indicated. Table 1 explains symbols used in these equations.

The infiltration rate is a function of the wetting front penetration depth and gets calculated as mass flux by

$$i_m = -k_s \cdot \frac{\Psi_{m_0}}{x_f(t)} - k_s \cdot g \tag{1}$$

This value can be divided by density of infiltrating fluid to obtain infiltration rate as volume flow rate.

70 $$i_v = i_m / \rho_q \tag{2}$$

The penetration depth of the wetting front is the integral function of the infiltration rate divided by the fillable pore space. An approximation of this integral function is used in EROSION-2D/3D:

$$x_f(t) = -\left(\left(\frac{k_s \cdot g \cdot t}{\rho_q \cdot \Delta \theta} \right) + \left(\frac{2 k_s \cdot \Psi_{mo} \cdot t}{\rho_q \cdot \Delta \theta} \right)^{0.5} \right) \tag{3}$$

Schmidt (1996) divided the wetting front in two independent fractions to derive Eq. (3). A stationary fraction is driven by

75 gravitational forces and is independent from time, whereas an instationary fraction is driven by matrix potential and is reduced with progression of the wetting front over time.

Parameters matrix potential and fillable pore space in Eq. (3) are determined from soil input parameters grain size distribution, bulk density, organic carbon content and initial water content using an estimation model by Van Genuchten (1980) in combination with pedo-transfer-functions by Vereecken (1989).

Table 1. List of symbols used in infiltration model equations.

symbol	meaning	unit
i_m	infiltration rate as mass flux	$\mathrm{kg\,m^{-2}\,s^{-1}}$
i_v	infiltration rate as volume flow	$\mathrm{m\,s^{-1}}$
k_{sat}	saturated hydraulic conductivity	$\mathrm{kg\,m^{-3}\,s^{-1}}$
k_s	saturated hydraulic conductivity, adjusted by skinfactor	$\mathrm{kg\,m^{-3}\,s^{-1}}$
Ψ_{m_0}	matrix potential	$\mathrm{J\,kg^{-1}}$
ψ_{m_o}	matrix potential	hPa
x_f	penetration depth of wetting front	m
t	time	s
g	gravitational constant	$9.81\,\mathrm{m\,s^{-2}}$
ρ_q	density of infiltrating fluid	$1000\,\mathrm{kg\,m^{-3}}$
ρ_b	bulk density of dry soil	$\mathrm{kg\,m^{-3}}$
θ_0	initial soil moisture	$V-\%$
θ_R	residual soil moisture	$V-\%$
θ_S	saturated soil moisture	$V-\%$
$\Delta\theta$	fillable pore space ($\theta_R - \theta_S$)	$V-\%$
α, n	parameters in Vereecken equations	-
CL, SI, SA	grain size fractions of clay, silt and sand	$M-\%$
C_{org}	content of organic carbon	$M-\%$
$b, \overline{D}, \sigma_p$	parameters in Campbell equations	-

$$\psi_{m_0} = \left(\left(\frac{\theta_S - \theta_R}{\theta_0 - \theta_R} - 1 \right) \cdot \frac{1}{\alpha^n} \right)^{1/n} \tag{4}$$

$$\theta_S = 0.81 - 0.283 \cdot 10^{-3} \cdot \rho_b + 0.001 \cdot CL \tag{5}$$

$$\theta_R = 0.015 + 0.005 \cdot CL + 0.014 \cdot C_{org} \tag{6}$$

$$\ln(\alpha) = -2.486 + 0.025 \cdot SA - 0.351 \cdot C_{org} - 2.617 \cdot 10^{-3} \cdot \rho_b - 0.023 \cdot CL \tag{7}$$

$$\ln(n) = 0.053 - 0.009 \cdot SA - 0.013 \cdot CL + 0.00015 \cdot SA^2 \tag{8}$$

$$\Delta\theta = \theta_S - \theta_0 \tag{9}$$

Because Eq.s 3 and 4 use different units for matrix potential a conversion is applied:

$$\Psi_{m_0} = \frac{\psi_{m_0} \cdot 100}{\rho_q} \tag{10}$$

According to Schindewolf (2012) the parameters α and n were determined in model versions prior 3.14 of EROSION-2D by

$$\log_{10}(\alpha) = -2.486 + 0.025 \cdot SA - 0.351 \cdot C_{org} - 2.617 \cdot 10^{-3} \cdot \rho_b - 0.023 \cdot CL \tag{11}$$

$$\log_{10}(n) = 0.053 - 0.009 \cdot SA - 0.013 \cdot CL + 0.00015 \cdot SA^2 \tag{12}$$

In case the input value of soil moisture θ_0 is higher θ_S or lower θ_R this value gets adjusted by EROSION-2D/3D to be slightly higher than θ_R or slightly lower than θ_S.

The equations used for estimation of saturated hydraulic conductivity are (compare Campbell, 1985):

$$k_{sat} = 0.004 \cdot \left(\frac{0.0013}{\rho_b} \right)^{1.3 \cdot b} \cdot exp(-0.069 \cdot CL - 0.037 \cdot SI) \tag{13}$$

$$b = \overline{D}^{-0.5} + 0.2 \cdot \sigma_p \tag{14}$$

$$log_{10}(\overline{D}) = \frac{CL}{100} \cdot log(0.001) + \frac{SI}{100} \cdot log(0.026) + \frac{SA}{100} \cdot log(1.025) \tag{15}$$

$$log_{10}(\sigma_p) = \sqrt{\frac{CL}{100} \cdot (log_{10}(0.001))^2 + \frac{SI}{100} \cdot (log_{10}(0.026))^2 + \frac{SA}{100} \cdot (log_{10}(1.025))^2 - (log_{10}(\overline{D}))^2} \tag{16}$$

2.2 Skinfactor

Skinfactor in EROSION-2D/3D is a calibration factor to the saturated hydraulic conductivity calculated by Eq. 13.

$$k_s = k_{sat} \cdot skin \tag{17}$$

Two methods of deriving the skinfactors from rainfall-runoff experiments were established in previous studies, both yielding slightly different values, resulting in different surface runoff rates. The first established method uses the skinfactor to adjust the amount of cumulative runoff from the plot area (skinfactor$_{runoff}$) (Michael, 2000). The second established method uses the skinfactor to adjust a certain infiltration rate, usually the final infiltration rate at the end of the experiment (skinfactor$_{inf}$) (Schindewolf and Schmidt, 2012). We used both methods to derive the skinfactors for the analysis. Transfer functions for the skinfactor$_{inf}$ showed a better fit to the validation datasets and are therefore presented in this study. To derive the skinfactor for each experiment, surface runoff curve is simulated by the EROSION-3D model. Infiltration module input parameters clay, silt, sand content, bulk density, initial soil moisture and organic carbon content measured during the experiment are entered in the model and skinfactor value is iteratively changed, until the end infiltration in case of skinfactor$_{inf}$ or cumulative runoff in case of skinfactor$_{runoff}$ match the measured data. Fig. 1 shows the infiltration curves calculated with EROSION-2D/3D

2.3 Rainfall-runoff data

An open database for storing, maintaining, and sharing protocols from rainfall-runoff experiments is being developed in parallel to this study (Deváty et al., 2020). Currently, the database contains protocols from three working groups: The Technical
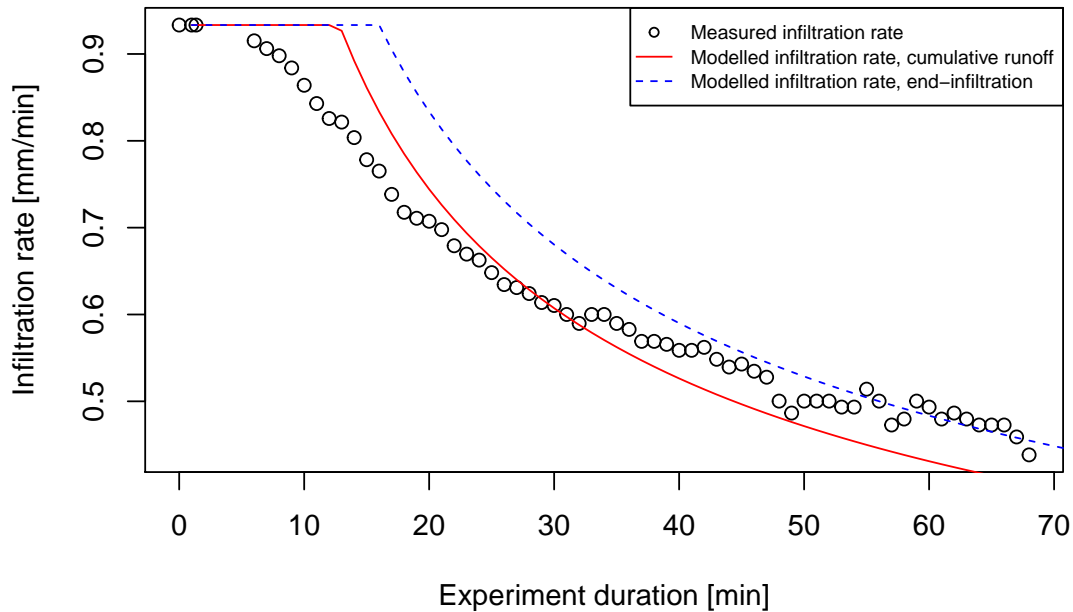
Figure 1. Modeled infiltration rates resulting from different methods of skinfactor determination. Calculated infiltration rate is limited by rainfall intensity [0.933mm/min].

University of Freiberg, Germany (TUBAF); the Research Institute for Soil and Water Conservation, Czech Republic (RISWC); and the Czech Technical University in Prague, Czech Republic (CTU). The database contains 464 experiments (126 from TUBAF, including the original 116 experiments used in previous studies, 191 from RISWC, and 147 from CTU), mainly from the central Czech Republic and the German state of Saxony. Experiments contained in the database were conducted for different projects and purposes. Not all experiments contain all input parameters required for skinfactor calibration, where the methodology of data acquisition and analysis can differ between working groups. The complete and consolidated dataset for statistical analysis contains 273 RISWC and TUBAF experiments. Parameters included in the statistical analysis and respective data acquisition methods used by the working groups are listed in Table 2.

2.4 Skinfactor prediction

The determined skinfactor values range from 0.001 to 100 in the dataset. The assumption of normally distributed residuals in the linear mixed effects models used in this study is violated when using untransformed skinfactors. Logarithmic transformation

Table 2. Parameters included in statistical analysis for skinfactor prediction.

parameter	method TUBAF	method RISWC	type of variable	category/unit
skinfactor	EROSION-3D iterative determination	EROSION-3D iterative determination	float	-
clay/silt/sand content*	no standard used - dispersion methods H2O, chemicals, ultrasound	pipeting method	float	$M - \%$
soil texture class*	soil texture triangle	soil texture triangle	factorial	clay/silt/loam/sand
organic carbon	combustion method of disturbed soil samples	Walkley-Black chromic acid wet oxidation method	float	$M - \%$
bulk density	dried soil core cylinders	dried soil core cylinders	integer	$\mathrm{kg\,m^{-3}}$
initial soil moisture	TDR-probe in field, repeated gravimetrical measurement of soil core cylinder	TDR-probe in field, repeated gravimetrical measurement of soil core cylinder 5-10 cm depth	float	$V - \%$
soil saturation	dry run - natural soil moisture conditions, wet run - after dry run reached steady infiltration and break up to one day	dry run same as FG, wet run - after 30 min dry run and 15 min break	factorial	dry /wet
crop	crop name	crop name	factorial	6 categories
vegetation cover	estimation in field	supervised picture classification	integer	%
management practice	manag. name	manag. name	factorial	conventional/conserv./no till.
plot ID**	same ID for dry/wet run during one campaign	same ID for dry/wet run during one campaign	factorial	ID number
working group**	group ID	group ID	factorial	TUBAF/RISWC

*The German KA5 classification system is used for soil texture (Sponagel and Ad-hoc-Arbeitsgruppe Boden (2005))

**Variables representing random effects in the used linear mixed effect models.

of skinfactors produces a near normal distribution for the residuals. Therefore, this transformation was used for all skinfactor values in the statistical analysis.

To determine the transfer functions for the skinfactor, linear mixed-effect models (Galecky and Burzykowski, 2013) were applied. All numerical soil input parameters and categorical variables used in previous studies were included in the analysis as fixed effects. Furthermore, two nested random effects were included in the model to account for the interdependency and hierarchy of the data. The first random effect is the working group. Results of the experiments can be affected by the use of a specific rainfall-runoff simulator. The rainfall parameters and methodology for data acquisition differ between the working groups (Table 2). The second random effect is the plot ID, which is nested in the working group. Both working groups usually repeat their measurements twice on an identical plot to obtain data under the dry and wet conditions. Measurements with the same plot ID are thus interdependent.

2.5 Model selection

Various models were fitted using the experimental dataset. Model ORIG, with factorial predictors originally used in the Parameter Catalogue (crop, management practice, dry/wet experiment, soil texture class, plant development), was fitted to statistically evaluate the current skinfactor prediction method available for model users (Michael et al., 1996). The dataset structures used in the Parameter Catalogue and presented in this study are not identical; therefore, the equivalents of the predictors were used to remain as close to the Parameter Catalogue approach as possible (e.g., factorial predictor plant development is not available for RISWC data; therefore, it was substituted by the numerical variable, vegetation cover). STEP1, STEP2 and STRONG represent the models manually selected using the stepwise method from the initial model containing all factorial predictors in the interactions with all numerical predictors. The manually controlled backward elimination approach was followed. Single predictors with the lowest significance were continuously removed from the model while controlling for the significance of the remaining predictors and interactions and the Akaike Information Criterion (AIC) (Akaike, 1987). STEP1 was the most complex model, whereas STEP2 and STRONG was selected by further elimination of least significant predictors and interactions from model STEP1 to provide more simple models for EROSION-2D/3D users according to their information on the study area and available predictors. The simplest model, i.e., STRONG, contains only the two most significant predictors.

2.6 Prediction validation

To examine statistical reliability of the fitted models a 10-fold cross validation approach was followed. The experimental dataset was divided into the training subset, containing 90% of the randomly selected experiments, and validation subset, containing the remaining 10% of the experiments. For the training subset coefficients of the functions were determined. The validation subset was then used to predict skinfactors. This procedure was repeated ten times assuring that each experiment was used for validation once. For each repetition model performance was evaluated by commonly used indicators. The overall quality of the transfer functions was calculated as average values of the indicators plus minus standard deviation. The indicators are: coefficient of determination (R^2), root mean square error (RMSE), mean and median absolute percent error (MAPE and MDAPE), and the ratio of the RMSE and the standard deviation of the measured data $STDEV_{obs}$ (RSR). MAPE works best if

there are no extremes or zeros in the dataset, MDAPE is independent from those values . According to (Moriasi et al., 2007), model performance is satisfactory if RSR <0.7, good if RSR <0.6, and very good if RSR <0.5.

In the second step, an error propagation of the predicted skinfactors for surface runoff and sediment mass was analysed. Soil and vegetation conditions from the experiments were applied on a hypothetical 400 m long and 9% steep slope. Surface runoff and sediment mass simulated with the experimentally derived skinfactor was compared to those simulated with the skinfactors predicted by presented models. The results were evaluated by the same indicators as in the first validaton step.

The last step of the validation was performed on real data collected on three 40 cm * 50 cm plots equipped with rainfall gauges, runoff trap devices, and soil moisture meters. The experimental site is situated in central Czechia (N $50° 24,41'$ E $14° 39,31'$). The plots were placed in a field of oilseed rape, two in the middle of the slope, one in the upper part of the slope. During the 2017 vegetation season, six rainfall events produced runoff. However, runoff was never recorded in all three plots, which shows high variability in the rainfall-runoff processes even within a very small area. The parameters of the events are presented in Table 3. Each rainfall event was modelled by Erosion-3D with the skinfactor predicted by transfer functions STEP1, STEP2 and STRONG; for each function, the skinfactor was corrected by the positive and negative MAPE error to account for the uncertainties in the predictions.

Table 3. Rainfall events used for the skinfactor validation.

date	initial moisture [%]	runoff volume [ml]	precipitation [mm]	max intensity [mm/5 min]	length [min]	saturation	comment
05.05.	28	0 - 20	4.4	0.6	50	dry	
14.05	27	0 - 100	12.8	7.4	390	dry	
29.06.	24	0 - 160	19	1	320	dry	crust
02.07.	38	0 - 40	3.2	0.4	190	wet	crust + wet
11.07.	28	0 - 30	3.2	0.2	180	dry	crust
15.07.	30	0 - 120	14	5.8	245	wet	crust

Saturation dry or wet was decided according to antecedent precipitation.

3 Results

3.1 Skinfactor prediction

Four models were fitted to evaluate the skinfactor estimation method given in the Parameter Catalogue and determine new transfer functions for predicting skinfactors using the most significant predictors (Fig. 2). Overview of the models is presented in Table 4. For each model predictors and coefficients of the pedotransfer function are provided, together with an evaluation of the model performance based on the validation dataset. The ORIG model, fitted to the predictor equivalents from the Parameter Catalogue, has low explanatory significance (variance explained by fixed effects R^2 = 0.14). Only soil saturation

180 (dry or wet experiment) is a highly significant predictor. The new transfer functions provide significant improvement to the accuracy of skinfactor prediction. Soil moisture and bulk density were determined as by far the most significant predictors (model STRONG), explaining together 82% of the skinfactor variability. The skinfactor increased with an increase in both of the predictors (Fig. 3). Other significant predictors, e.g., silt content, vegetation cover, soil texture group, and soil saturation, slightly improved the model fit. The most complex STEP1 model containing all of the significant predictors, including the
185 interactions (see Table 4), explains only an additional 3% of the skinfactor variability. STEP2 was simplified by removing factorial predictor soil texture class, numerical predictor vegetation cover and all interactions from STEP1, STRONG contains only initial soil moisture and bulk density.

All the new transfer functions performed well according to the interpretation of the RSR indicator by Moriasi (2007). The median absolute percent error was between 30% and 34% for the new transfer functions while it was 71% for the ORIG
190 function. Except MAPE which is highly prone to extremes, all indicators showed the most complex STEP1 model as the best performing, while the most simple STRONG model as least performing. The differences are, however very small.

3.2   Error propagation

Error propagation of the predicted skinfactors to the surface runoff and sediment mass simulated by EROSION-3D was evaluated on the hypothetical 400 m long slope. Table 5 statistically compares the model performance. Simulations with the
195 skinfactors predicted by ORIG model produced no runoff for 71 out of the 273 datasets while the new transfer functions produced no runoff only for 3–9 datasets. The median error of the surface runoff was 34–40% while that of the sediment mass was 41–49% (for the ORIG model these were 78 and 95%, respectively). Errors below 100% characterised 86% of the datasets for surface runoff and 82% of the datasets for sediment mass, whereas, for the ORIG model, these values were 62 and 55%, respectively. STEP1 was the best performing model for both the surface runoff and sediment mass prediction (as compared with
200 ORIG in Figs. 4 and 5). Error distribution illustrated in fig. 6 further shows, that there is almost no difference between STEP 2 and STRONG. The results indicates major impact of the two strongest predictors, i.e., initial soil moisture and bulk density and significant improvement of the model performance when interaction with soil texture and impact of previous rainfall is considered. In general, all of the new transfer functions showed significantly better performance than the original approach, such that they can be used to predict the skinfactor.

205 ### 3.3   Validation with real events

Real rainfall-runoff events were modelled using the new transfer functions. To account for the potential error in the functions, each event was simulated with the predicted skinfactor and the skinfactor corrected by +MAPE error and -MAPE error. EROSION-3D simulated no runoff for four out of the six events using all of the transfer functions. Simulations with the skinfactor corrected by MAPE to increase the infiltration rate, produced no runoff for all events. Only events 14.5. and 15.7. produced
210 runoff (Table 3). For all of the transfer functions, the modelled runoff was within the range or close to the runoff value recorded by the trap devices. The STRONG model simulated less runoff than the other models and only the simulations with skinfactor decreased by MAPE produced runoff. The recorded runoff values for events 5.5., 2.7., and 11.7. are questionable, because the

Table 4. Linear mixed effects models for skinfactor prediction: model evaluation based on the validation dataset using common statistical indicators, model variables, and their coefficients.

	ORIG	STEP1	STEP2	STRONG
R^2	0.14 ± 0.07	0.85 ± 0.08	0.83 ± 0.09	0.82 ± 0.09
RMSE	2.09 ± 0.22	0.88 ± 0.28	0.97 ± 0.32	1.01 ± 0.31
RSR	0.93 ± 0.03	0.39 ± 0.11	0.43 ± 0.11	0.45 ± 0.1
MAPE	1.4 ± 0.52	0.7 ± 0.25	0.62 ± 0.21	0.65 ± 0.24
MDAPE	0.71 ± 0.19	0.3 ± 0.13	0.32 ± 0.08	0.34 ± 0.1
Intercept	-2.7909	-35.7264	-17.4628	-16.5647
Initial soil moisture	—	0.3195	0.1819	0.1719
bulk density	—	0.012	0.0072	0.0074
silt	—	0.1499	0.0174	—
vegetation cover	-5×10^{-4}	0.01	—	—
soil saturation- wet	1.5767	-2.0971	-0.2851	—
soil texture class- sandy	-0.9513	24.4281	—	—
soil texture class- silty	-0.4632	17.8491	—	—
type of management practice- conventional tillage	-0.2381	—	—	—
type of management practice- no tillage	0.0098	—	—	—
type of crop- cereals	1.6397	—	—	—
type of crop- erosion permitting crop	1.4584	—	—	—
type of crop- legume	1.3115	—	—	—
type of crop- oilseed crop	0.6706	—	—	—
type of crop- seedbad	1.6648	—	—	—
wet soil saturation : silt	—	0.0208	—	—
wet soil saturation : initial soil moisture	—	-0.0811	—	—
wet soil saturation : bulk density	—	0.0021	—	—
wet soil saturation : cover	—	-0.0053	—	—
sandy soil texture class : silt	—	-0.1655	—	—
silty soil texture class : silt	—	-0.1331	—	—
sandy soil texture class : bulk density	—	-0.0087	—	—
silty soil texture class : bulk density	—	-0.0056	—	—
sandy soil texture class : initial soil moisture	—	-0.0945	—	—
silty soil texture class : initial soil moisture	—	-0.0806	—	—
sandy soil texture class : cover	—	-0.006	—	—
silty soil texture class : cover	—	-0.005	—	—

— indicates not included in the model.

A:B indicates interaction between factors A and B.

An example of transfer function construction (STEP2): $skinfactor = e^{-17.4628 + 0.0174*silt + 0.0072*bulkdensity + 0.1819*initialsoilmoisture - 0.2851*wet}$
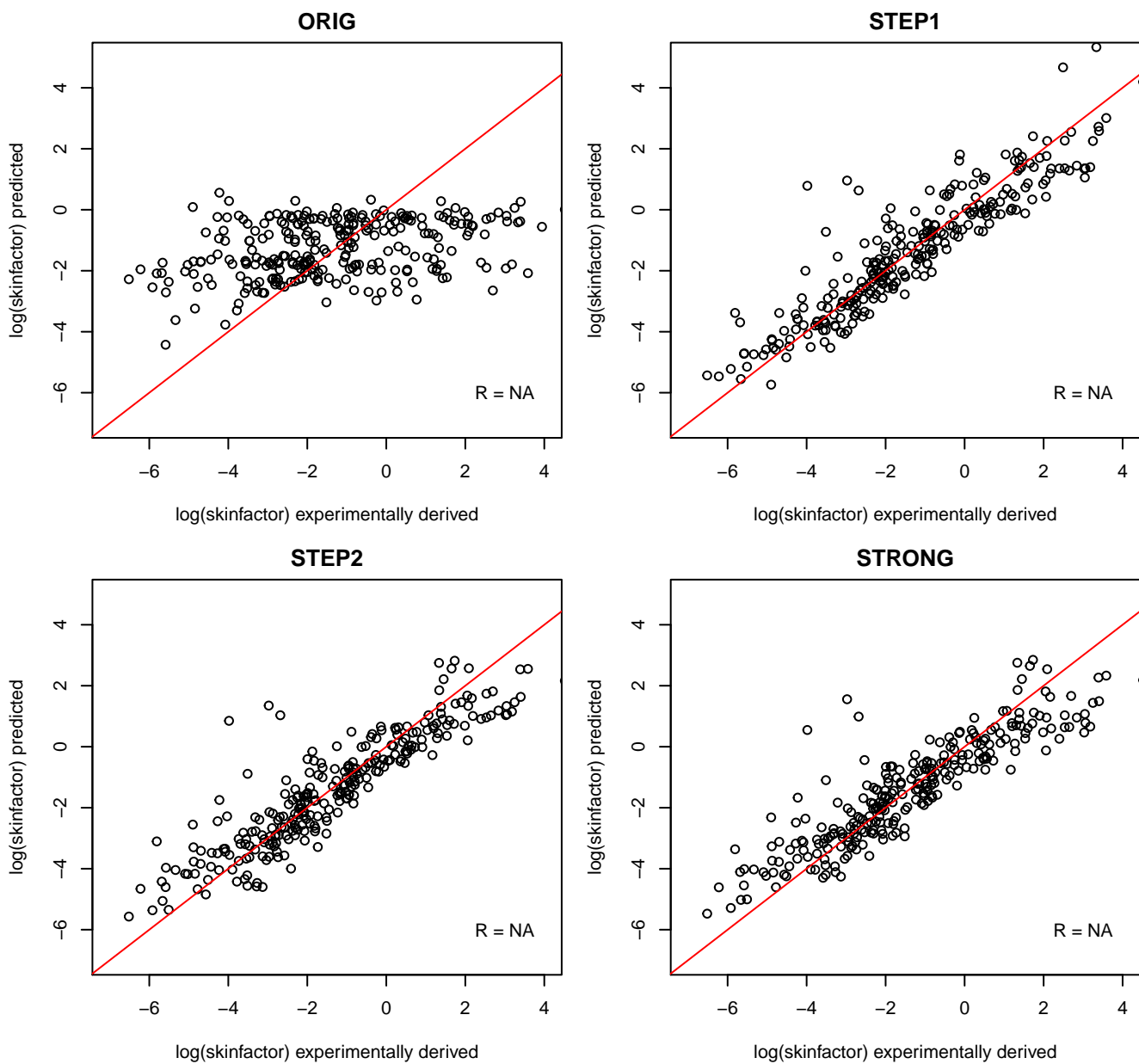
Figure 2. Experimentally derived versus predicted skinfactors (log values) for selected validation dataset.
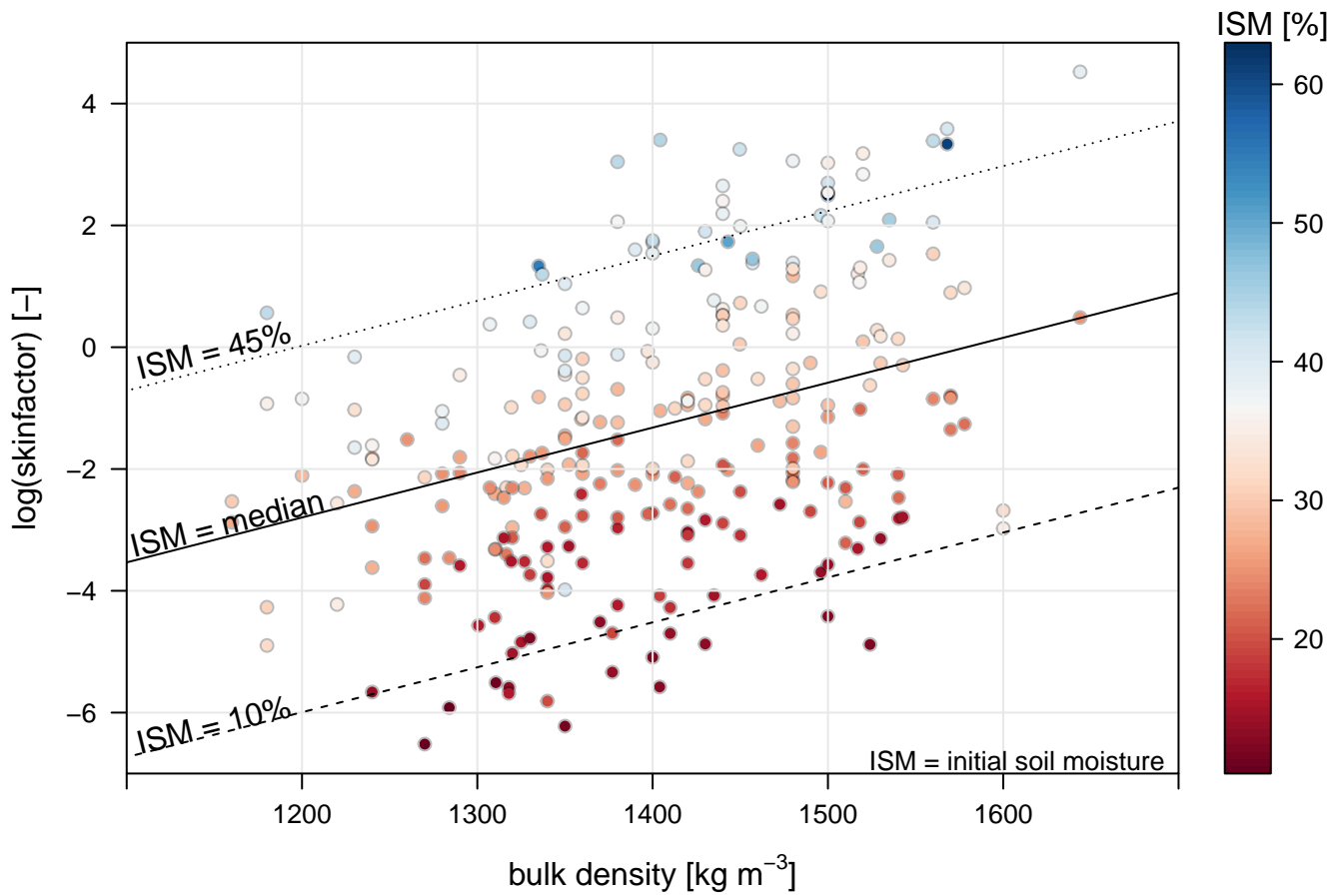
Figure 3. The dependency of the skinfactor on the bulk density and soil moisture. Point data represent whole dataset with experimentally derived skinfactors. Line data represent skinfactor prediction by STRONG for three different initial soil moisture conditions. ISM = initial soil moisture.
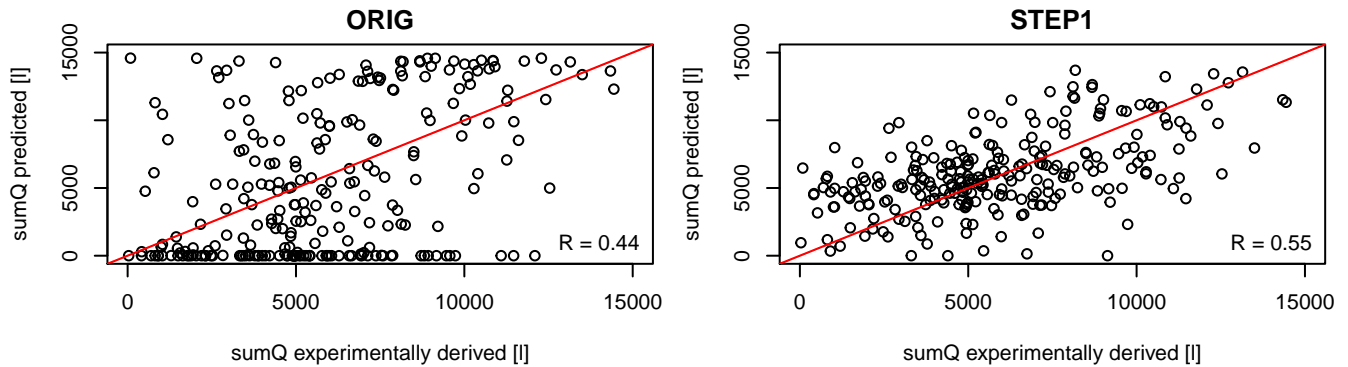
Figure 4. Surface runoff simulated with the derived skinfactor versus the ORIG skinfactor (left) and STEP1 skinfactor (right).
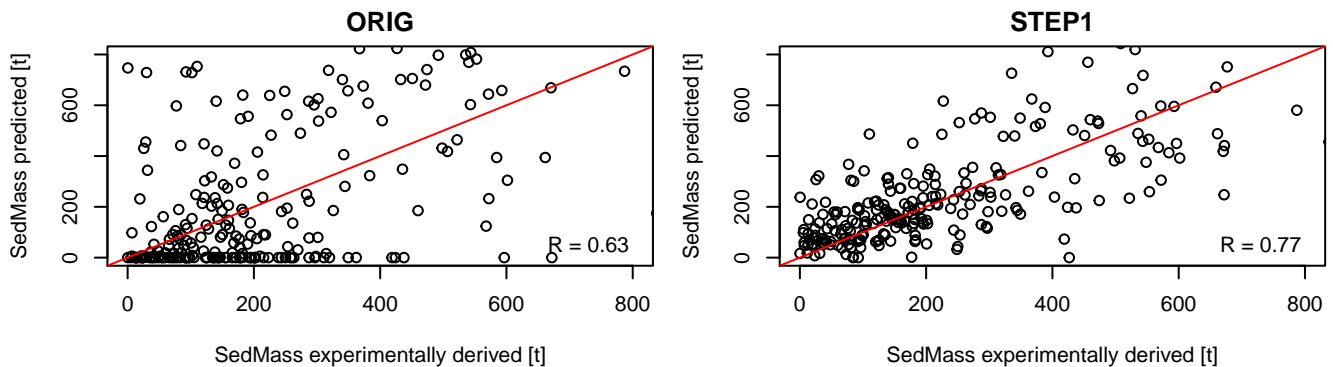
Figure 5. Sediment mass simulated by EROSION-3D with the experimentally derived skinfactor versus skinfactor predicted by ORIG model (left) and STEP1 model (right).

rainfall data had very low volume and intensity, significantly lower than the erosion causing rainfall, as defined by (Janeček et al., 2012) (12.5 mm volume or 6 mm/15 min intensity). Event 29.6. had one of the highest volumes, but had a relatively
215 long duration and low intensity. While this event produced the largest runoff, as recorded by a trap device, EROSION-3D simulated no runoff. Crust on the topsoil was recorded by field workers for the last four events, which likely initiated runoff from the low-volume and low-intensity rainfall events. The fact that runoff was never recorded in three trap devices during the same event shows the high natural variability of the rainfall-runoff process within a small area. More validation datasets for testing EROSION-3D under variable soil and vegetation conditions are required to properly validate the transfer functions.
220 Validation at the field or the catchment scale is appropriate because the measured runoff data represent average conditions, where site-to-site changes, as recorded using the trap device, are blurred.
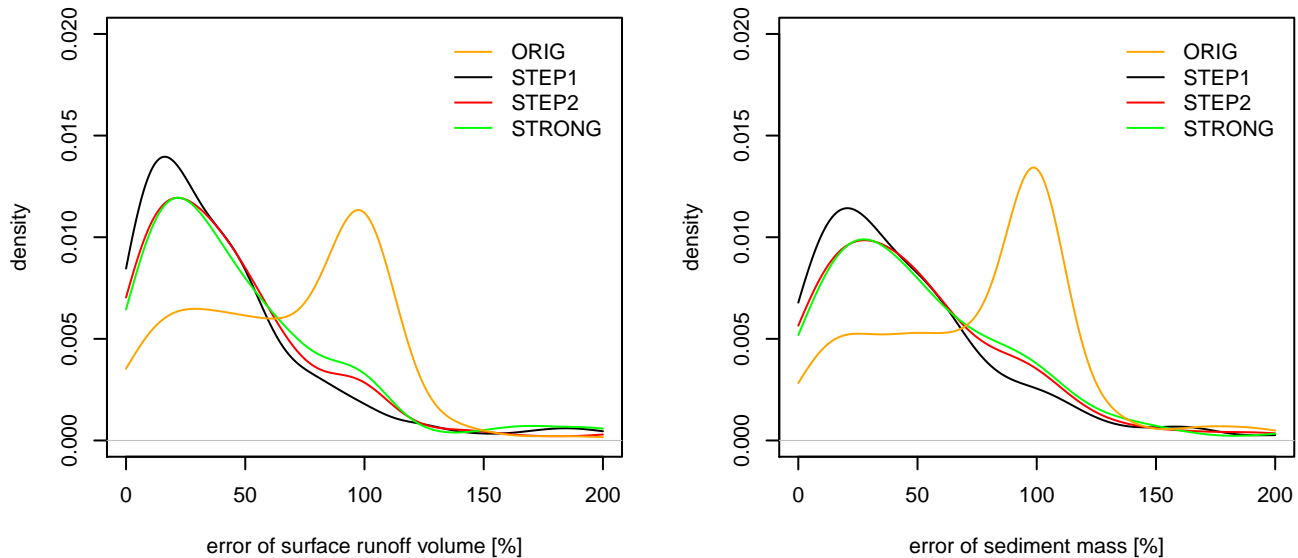
Figure 6. Error propagation of skinfactor prediction in the surface runoff (left) and sediment mass (right), a density plot of the percent error. Outlying experiments (error > 200%) create 6–9% of the validation experiments. Experiments with no simulated runoff is evaluated as 100% error, which explains the significant peak in ORIG model.

3.4 Discussion

The joint rainfall simulation dataset of TUBAF and RISWC provides a sufficient amount of data to statistically analyze the relationships between the skinfactor calibration parameter and commonly measured soil and vegetation conditions, as well
225   as to derive the transfer functions for the skinfactor. It is however important to consider the spatial limitation of the transfer functions given by the dataset, which consists of data representing soils of The Czech Republic and Saxony (state of Germany). Other open databases of rainfall-runoff experiments covering bigger spatial variability exist (e.g. Seibert et al. (2011), Rahmati et al. (2018)), however, all of the experiments except those made by model developers are lacking at least one of the required input parameters.

230   The current skinfactor prediction method published in the Parameter Catalogue is based on easily and accurately measurable factorial variables, i.e., crop, management practice, soil saturation, development stage of vegetation, and soil texture class. The results of model ORIG show that out of these variables only soil saturation had statistically evident influence on the skinfactor. This parameter distinguishes only two categories of soil saturation – dry soils (no antecedent precipitation) and wet soils (shortly after precipitation), indicating rather impact of previous rainfall, than the soil moisture itself. The relationship was
235   explained by stability of aggregates (Michael, 2000). Dry aggregates are prone to destruction by enclosed air, which becomes

Table 5. Error propagation of the skinfactor prediction models for the surface runoff and sediment mass evaluated by commonly used statistical indicators.

	ORIG	STEP1	STEP2	STRONG
surface runoff prediction				
no runoff simulated	71	3	8	9
outliers (error > 200%)	14	20	24	22
R^2	0.19	0.3	0.2	0.2
RMSE	4875	2840	3211	3363
RSR	1.58	0.92	1.04	1.09
MDAPE*	0.78	0.34	0.39	0.4
sediment mass prediction				
R^2	0.4	0.59	0.51	0.51
RMSE	283	161	181	196
RSR	1.16	0.66	0.74	0.81
MDAPE*	0.95	0.41	0.48	0.49

MDAPE: median absolute percent error. The median, instead of the mean, was used because of zero runoffs and outliers.

Table 6. Runoff volume [mL] from real rainfall events, measured versus simulated with the skinfactors predicted by the new transfer functions.

date	measured sumQ	STEP1 sumQ	STEP2 sumQ	STRONG sumQ
14.05	0 - 100	0 / 13 / 122	0 / 13 / 115	0 / 0 / 83
15.07.	0 - 120	0 / 108 / 271	0 / 0 / 148	0 / 0 / 22

Measured sumQ: min - max value measured in three trap devices. Predicted sumQ: predicted - MAPE error / predicted / predicted + MAPE error.

compressed by water infiltrating into the aggregates. The smaller particles from the destroyed aggregates then cause surface sealing and smaller skinfactors.

Further studies using numerical variable initial soil moisture observed relationship of skinfactor and soil moisture corresponding with our results. It was however again explained by state of the soil before and after rainfall. Schindewolf and Schmidt (2012) used air trapping on a larger scale as explanation. Air trapping occurs when the wetting front enters the soil. The enclosed soil air then hinders, to a certain extent, the infiltration. A further theoretical explanation was hydrophobicity, which results from hydrophobic particles (mainly organic matter) in the soil matrix. Once dried, particles are harder to rewet than hydrophilic particles (Hallett, 2007; Seidel, 2008; Kuhnert, 2008; Schindewolf, M.; Schmidt, 2009). All of these effects would decrease the infiltration rates for dry soils. Our study indicates, that these theories explain only smaller part of the skin-

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245   factor variability as the categorical soil saturation is only a weak predictor (compare models STEP1 and STRONG) and the relationship with initial soil moisture seems to be independent from dry or wet experiment conditions.

    This study followed the state-of-the-art parametrisation method established with EROSION-3D and used linear mixed effect models to find relationships between the parameter and soil and vegetation conditions. The derived pedotransfer functions showed strong logarithmic relationship between skinfactor and soil moisture, which indicates drastic overestimation of infil-

250   tration of dry soils by EROSION-2D/3D. This arise questions regarding the used method of parametrisation. The established approach fits infiltration curves by scaling only one of the Green-Ampt parameters - saturated hydraulic conductivity, this value is estimated by equations 13 and calibrated through skinfactor. As a consequence the parametrisation focused only to this single parameter.

    The Green-Ampt parameter water potential at the wetting front is assumed to be equal to matrix potential of the soil at an-

255   tecedent water content in EROSION-2D/3D and is calculated by equation 4. The water potential at the wetting front is however only a week function of the matrix potential when the soil is dry (Dingman, 2015). This leads to an overestimation of the infiltration rate of dry soils, which is in turn compensated by decreasing saturated hydraulic conductivity to extremely small values.

    To get better insight in the parameter fitting strategy Monte Carlo parameter optimization (Luengo et al., 2020) was tested,

260   where both Green-Ampt parameters saturated hydraulic conductivity and water potential at the wetting front were varied and their optimal combination to fit measured infiltration curve were searched. Runoff measurement of a single experiment on a silty loam with an initial volumetric soil moisture content of 31 % was used as fitting target. The matrix potential estimated by equation 4 for this experiment equals a pF-value of 2.13 and the saturated hydraulic conductivity as estimated by equation 13 equals $1.1 \times 10^{-4} kg/m^3/s$. In the state-of-the-art parametrization method the saturated hydraulic conductivity was adjusted

265   by skinfactor to $1,7x10^{-4}$ kg/m^3/s in case of fitting end infiltration and to $1,4x10^{-4}$ kg/m^3/s in case of fitting cumulative runoff. In the Monte Carlo approach 10000 randomly sampled combinations of the parameters were modelled with EROSION-3D. The parameter combination at which the RMSE of simulated and measured infiltration curve was the smallest represents the best found fit (pF = 1.38, ks = $6,6x10^{-4}$ kg/m^3/s). The two methods are compared in Fig. 7. While the parameter optimization method is able to adequately simulate the infiltration curve in its whole extent, the single parameter method

270   show underestimation of infiltration in whole extent in case of fitting end infiltration and underestimation at the beginning and overestimation at the end of experiment in case of fitting cumulative runoff.

    Nevertheless the parametrisation method behind this study is not optimal, the presented functions to estimate skinfactor indicates significant improvement in the infiltration module performance in comparison with the values presented in parameter catalog (compare results of model ORIG with the new pedotransfer functions). The validation on real data indicates good

275   model preformeance for rainfalls with higher intensity and volume. Model users should use the functions carefully and with the awareness of an error introduced in the parametrisation phase. At the same time results of the study are opening a way for further EROSION-2D/3D development which can be approached either through the algorithms implemented in the source code of EROSION-3D or through different method of model parametrisation. The very basic approach to optimize parameters of the
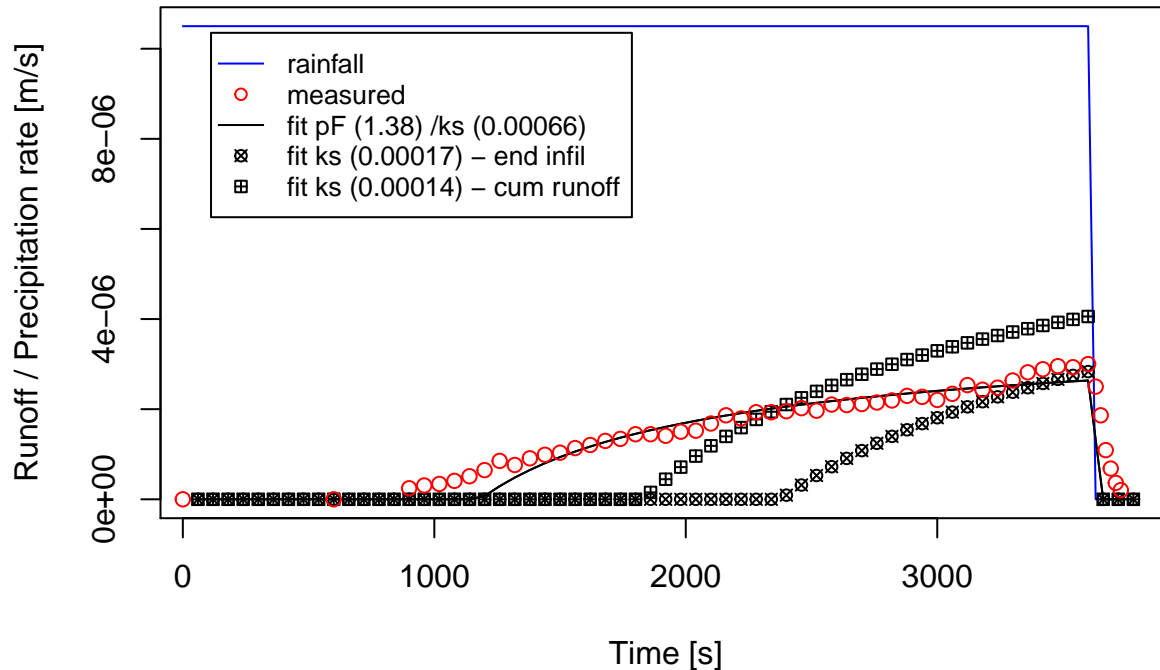
Figure 7. Comparison of parameter fitting strategies: ks fit refers to variation of hydraulic conductivity $[kg/m^3/s]$ only (state-of-art in EROSION-3D) with a fixed pF value of 2.13, estimated from initial soil moisture. Fit of pF/ks refers to best simulation found by Monte Carlo simulation.

Green-Ampt approach in EROSION-3D applied in this study can be seen as first step towards the use of advanced parameter
280   optimization algorithms (e.g. the SPOTPY package (Houska et al., 2015)).

4   Conclusion

This study aimed to increase the accuracy of the infiltration module of the EROSION-2D/3D soil erosion simulation tool by introducing new transfer functions to estimate the calibration parameter adjusting saturated hydraulic conductivity called skinfactor. The relationship of the skinfactor with soil, vegetation, and farm management parameters was analysed using
285   the linear mixed effect models based on 273 rainfall-runoff experiments. The initial soil moisture and bulk density were found to be the most important predictors, together explaining 82% of the skinfactor variability. These parameters are not considered in currently available prediction methods provided in (Michael et al., 1996). Other significant predictors such

as soil texture (i.e., the silt content and KA5 soil texture group), vegetation cover and the impact of previous rain events slightly improved the skinfactor prediction. Four transfer functions with different complexities and number of predictors to predict skinfactor were presented, such that the users can make a selection according to the available data in their study area. The proposed transfer functions present significant increase in the skinfactor prediction accuracy, as compared with currently available methods (decrease in the MDAPE error from 71 to 30–34%). Error propagation of the estimated skinfactors indicates substantial improvements to surface runoff and soil loss simulations. The strong logarithmic relationship of skinfactor with soil moisture however show a misinterpretation of the Green-Ampt algorithms in the EROSION-2D/3D. A wrong assumption that the water potential at the wetting front is equal to the initial water potential in soil had to be compensated by the skinfactor which is as a consequence highly related to initial soil moisture. Different parameter optimization method was tested, where the best combination of both parameters, saturated hydraulic conductivity and water potential at the wetting front are searched. Both parameters can be than predicted from soil parameters based on pedotransfer functions. This finding paves a direction of further EROSION-2D/3D model development promising further improvement in the infiltration model accuracy.

Code and data availability. This paper was compiled using the RMD-template by Nuest (Allaire et al., 2020) in RStudio (RStudio Team, 2020). The source file with all calculations performed in R (R Core Team, 2020) and not open accessible input data are available in the supplementary materials.

Author contributions. AR, JD, MM, and AB made rainfall experiments, HB, JL and JD processed rainfall experiments data, JL automated skinfactor determination, HB, JL and JD made the statistical analysis, IG provided data for validation on real events, HB and JL wrote the code and prepared manuscript, AR and JK consulted the whole process.

Competing interests. The authors declare no competing interests.

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