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 ~~is adjusted by calibration of the skinfactor parameter~~ 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 ~~presents new~~ 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 ~~that significantly improve~~ significantly improving the accuracy of the infiltration module and thus the overall EROSION-2D/3D model performance ~~. The transfer functions are based on a statistical analysis of the rainfall-runoff simulation database, which contains 273 experiments compiled by two independent working groups. Linear mixed effects models, with a manual backward elimination approach for the predictor selection, were applied to derive the transfer functions.~~ are provided in this study. Soil moisture and bulk density were identified as the most significant predictors explaining ~~79~~82% of the skinfactor variability, followed by the soil texture, vegetation cover and the impact of previous rainfall events. The ~~mean~~ median absolute percentage error of the skinfactor prediction was improved from ~~192~~71% using the currently available method, to ~~66~~30-34% using the presented transfer functions~~. Error propagation of the predicted skinfactors into the surface runoff and soil loss on the hypothetical slope showed significant improvement in~~ , 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 iniftration 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 ~~results. A first validation of real rainfall-runoff events indicates good model performance for events with a higher total precipitation and intensity~~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, homogenous, and permanent submerged soil column, which does not usually allow the simulation of natural conditions without additional calibration parameters or advanced algorithms. 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 ~~or infiltration~~ experiments with the hillslope simulation tool EROSION-2D (Michael et al., 1996). This process requires extended time and demands manual labour, 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 ~~factorial~~ 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 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 analyse the relationships between the skinfactor and other parameters 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. ~~This paper reports the skinfactor transfer functions derived from currently available data; however, this process is fully reproducible using the R code provided in the supplementary material of this paper, such that the functions can be improved and more robustly validated using the growing dataset of rainfall simulations.~~

2 Data and methods

2.1 ~~Skinfactor~~Infiltration module

The infiltration ~~submodule~~ model used in EROSION-2D/3D was developed by ~~Schmidt (1996)~~ Schmidt (1996) based on the Green-Ampt infiltration approach (Green and Ampt, 1911)~~, which includes a simplification of the infiltration process by assuming that rainwater penetrates the soilin a piston-like flow and completely saturates the available~~. 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.

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

The penetration depth of the wetting front is the integral function of the infiltration rate divided by the fillable pore space. ~~Empirical functions are used to estimate the matrix potential (Vereecken et al., 1989; Van Genuchten, 1980) and saturated hydraulic conductivity (Campbell, 1985). A full description of the infiltration submodule is given in Schmidt (1996). As the~~

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

symbol	meaning	unit
$\mathrm{i_m}$	infiltration rate as mass flux	$\mathrm{kg\,m^{-2}\,s^{-1}}$
$\mathrm{i_v}$	infiltration rate as volume flow	$\mathrm{m\,s^{-1}}$
$\mathrm{k_{sat}}$	saturated hydraulic conductivity	$\mathrm{kg\,m^{-3}\,s^{-1}}$
$\mathrm{k_s}$	saturated hydraulic conductivity, adjusted by skinfactor	$\mathrm{kg\,m^{-3}\,s^{-1}}$
$\Psi_{\mathrm{m_0}}$	matrix potential	$\mathrm{J\,kg^{-1}}$
$\psi_{\mathrm{m_o}}$	matrix potential	hPa
$\mathrm{x_f}$	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	$\mathrm{V-\%}$
θ_{R}	residual soil moisture	$\mathrm{V-\%}$
θ_{S}	saturated soil moisture	$\mathrm{V-\%}$
$\Delta\theta$	fillable pore space $(\theta_{\mathrm{R}}-\theta_{\mathrm{S}})$	$\mathrm{V-\%}$
α, n	parameters in Vereecken equations	-
$\mathrm{CL, SI, SA}$	grain size fractions of clay, silt and sand	$\mathrm{M-\%}$
$\mathrm{C_{org}}$	content of organic carbon	$\mathrm{M-\%}$
$\mathrm{b}, \overline{\mathrm{D}}, \sigma_{\mathrm{p}}$	parameters in Campbell equations	-

~~theoretical concept of infiltration assumes a rigid soil matrix, time variable structural processes, such as soil compaction, slaking, and crusting or macropores due to shrinking and biological activities, should be considered using an empirical factor, known as the skinfactor. This factor is used to adjust the~~ An approximation of this integral function is used in EROSION-2D/3D:

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

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

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

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

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

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

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

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

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 in between θ_R and θ_S.

The equations used for estimation of saturated hydraulic conductivity ~~according to Schindewolf and Schmidt (2012) as follows:~~

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

are (compare Campbell, 1985):

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

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

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

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

~~where is~~

2.2 Skinfactor

Skinfactor in EROSION-2D/3D is a calibration factor to the saturated hydraulic conductivity ~~as calculated by Campbell estimation, is saturated hydraulic conductivity adjusted by skinfactor , and is skinfactor .~~ calculated by Eq. 13.

~~Values~~

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

According to (Michael, 2000) values of the skinfactor <1 reduce the infiltration rate to consider the effects of soil slaking and crusting, as well as anthropogenic compaction. Values of the skinfactor >1 cause a positive correction of the infiltration rate, e.g., to consider increased infiltration in macropores due to soil shrinking, biological activity, or tillage impact. 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~~ first established method uses the skinfactor to adjust the amount of cumulative runoff from the plot area ($\text{skinfactor}_{\text{runoff}}$) (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 ($\text{skinfactor}_{\text{inf}}$) (Schindewolf and Schmidt, 2012). ~~The best method remains a topic of debate among model developers. In this study, we~~ We used both methods to derive the skinfactors for the analysis. Transfer functions for the $\text{skinfactor}_{\text{inf}}$ 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 $\text{skinfactor}_{\text{inf}}$ or cumulative runoff in case of $\text{skinfactor}_{\text{runoff}}$ 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 (Devátý et al., 2020). Currently, the database contains protocols from three working groups: The Technical

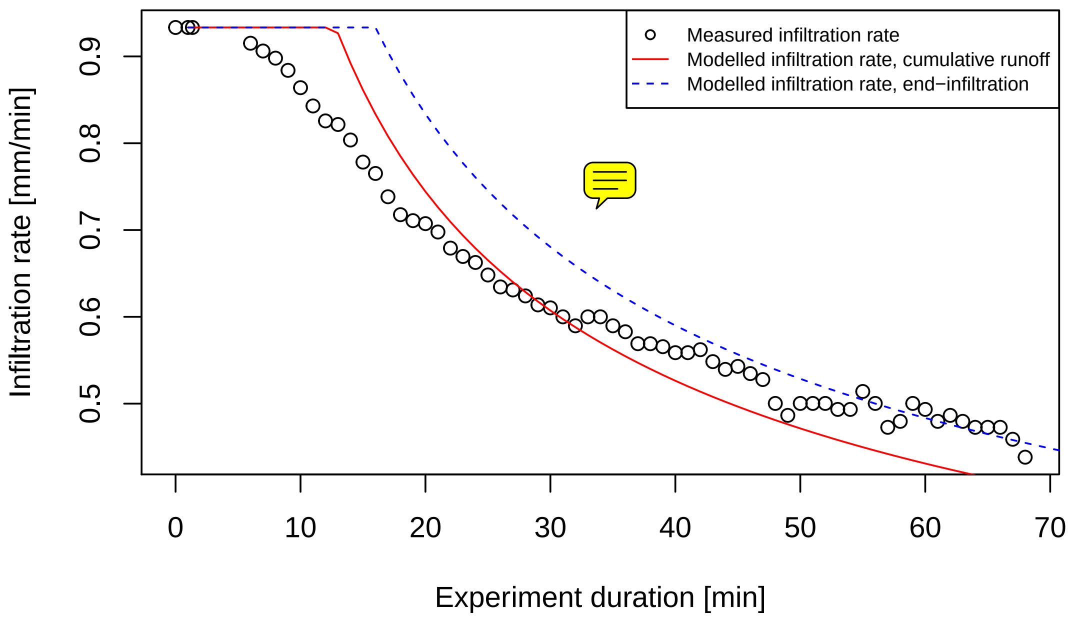

Figure 1. Modeled infiltration rates resulting from different methods of skinfactor determination. Calculated infiltration rate is limited by rainfall intensity [0.933mm/min].

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 ~~CTU data do not contain organic carbon content and bulk density and were thus not used in this study. Another 44 RISWC and TUBAF experiments were excluded from further analysis due to missing input parameters, no generated runoff, or the use of non-standard experimental conditions. Factorial predictors of crops and management practices were fractionated into many levels represented by a few to tens of cases. For better statistical representation, the predictors were categorized into subgroups based on their similar behaviour during the erosion process (Table ??). 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.

~~Reduction of factorial variables Crop and Management practice. seedbed seedbed~~
~~erosion permitting crop maize, potatoes, root beet, sunflower~~
~~legume broadbean, peas, flax, lupine~~
~~oilseed crop white mustard, oilseed rape~~
~~cereals spring barley, winter barley, spring wheat, winter wheat, winter rye, panic grass~~
~~catch crop, erosion restricting crop ryegrass, field pea, buckwheat, purple tansy conventional tillage (CvT) CvT, CvT with removed stones, CvT after grass, CvT with undersowing~~
~~conservational tillage low tillage, chiselled, vertical tillage after field pea, vertical tillage after white mustard, vertical tillage after purple tansy~~
~~no tillage (NT) NT to mulch, NT after desiccated white mustard, NT after desiccated ryegrass, NT after desiccated field pea, NT after desiccated purple tansy~~

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

	method RISWC	type of variable	category/unit
SION-3D on	~~EROSION-2D~~ EROSION-3D iterative determination	float	-
ispersion icals,	pipetting method	float	$M - \%$
	soil texture triangle	factorial	clay/silt/loam/sand
of es	Walkley-Black chromic acid wet oxidation method	float	$M - \%$
ders	dried soil core cylinders	integer	$kg\,m^{-3}$
repeated rement of	TDR-probe in field, repeated gravimetrical measurement of soil core cylinder 5-10 cm depth	float	$V - \%$
moisture after dry nfiltration day	dry run same as FG, wet run - after 30 min dry run and 15 min break	factorial	dry /wet
	crop name	factorial	6 categories~~(see Table ??)~~
	supervised picture classification	integer	%
	manag. name	factorial	~~3 categories (see Table ??)~~conventional/conserv./no till.
run during	same ID for dry/wet run during one campaign	factorial	ID number
	group ID	factorial	TUBAF/RISWC

2.4 Skinfactor prediction

The ~~skinfactor has a nearly logarithmic distribution, with values ranging~~ 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 of skinfactors produces a near normal distribution for the residuals. Therefore, this transformation was used for all skinfactor values in the statistical analysis.

~~The dependency of the skinfactor on single predictors was tested in the correlation matrix for the numerical predictors and via an ANOVA analysis for the factorial predictors to obtain the first insight into the relationships. Numerical variables of the initial soil moisture, bulk density, and soil texture were correlated with the skinfactor. Multicollinearity was observed between the sand and silt content and between the vegetation cover and time of consolidation. The sand content was removed as the soil texture predictor has less of a correlation with the skinfactor than the silt content. The time of consolidation was removed as a parameter because it is harder to obtain for model users than the vegetation cover. Among the factorial variables, the significant impact that soil saturation (dry/wet experiments) has on the skinfactor was detected, which corresponds to the correlation between the skinfactor and the initial soil moisture. Dry soil leads to lower skinfactors than saturated soils. However, it is important to consider the soil saturation not only in the context of the soil moisture (low x high), but also in the context of the state of the topsoil. While dry experiments represent the natural conditions of the soil cover, wet experiments represent the soil cover after rainfall and impacts from the destruction of soil aggregates and soil crust, loss of trapped air, or water repellence. The crop type and soil texture group also have an impact on the skinfactor, but only on the inter-level stage. For the crop predictor, unlikely relations were observed. Differences between similar crop groups (e.g., catch crops versus cereals) were more significant than the differences between highly diverse crop groups (e.g., catch crops versus seedbed). Significantly different skinfactor values were also observed between working groups.~~

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

~~The experimental dataset was divided into the training subset, containing 75% of the randomly selected experiments, and validation subset, containing the remaining 25% of the experiments.~~ Various models were fitted using the ~~training subset~~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–STEP3 represent the group of~~ 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)~~and the environmental sensitivity of the selected predictors~~. STEP1 was the most complex model, whereas STEP2 and ~~STEP3 were selected by simplifying~~ STRONG was selected by further elimination of least significant predictors and interactions from model STEP1 to provide ~~a suitable model~~ 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

~~Statistical~~ To examine statistical reliability of the fitted models ~~was measured based on the validation dataset, consisting of the remaining 25~~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 ~~experimental data. In the first step of validation, skinfactors were predicted by transfer functions and compared to the experimentally derived skinfactors. In the second step, an error propagation of the predicted skinfactors for surface runoff and sediment volume was analysed. Soil and vegetation conditions from the validation datasets were applied on a hypothetical 400 m long and 9% steep slope. Surface runoff and sediment volume simulated with the experimentally derived skinfactor was compared to the simulated skinfactor results. The goodness-of-fit of the measured and predicted skinfactor values was evaluated with commonly used indicators~~ 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 $\mathrm{STDEV_{obs}}$ (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 ~~STEP1–3~~ 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

~~Five~~ 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). ~~Table 4 lists the~~ 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~~and the model predictors with the coefficients for transfer function construction~~. The ORIG model, fitted to the predictor equivalents from the Parameter Catalogue, has low explanatory significance (variance explained by fixed effects R^2 = ~~0.12~~0.14). Only soil saturation (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 ~~79~~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 interactions (see Table 4), explains only an additional ~~4~~3% of the skinfactor variability. ~~All four~~ 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 et al., 2007). The mean~~ Moriasi (2007). The median absolute percent error was between ~~66% and 72~~30% and 34% for the new transfer functions while it was ~~192~~71% for the ORIG 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~~

3.2 Error propagation

Error propagation of the predicted ~~skinfactor for~~ skinfactors to the surface runoff and sediment ~~volume~~ mass simulated by EROSION-3D was evaluated on the hypothetical 400 m long slope. ~~The skinfactors input into~~ Table 5 statistically compares the model performance. Simulations with the skinfactors predicted by ORIG model produced no runoff for ~~24~~ 71 out of the ~~64 validation~~ 273 datasets while the ~~skinfactors input into the~~ new transfer functions produced no runoff only for ~~1–3 datasets(Fig. 4). There is not a large difference in the error propagation between models STEP1–3 and STRONG (Fig. 6). This indicates the major impact of the two strongest predictors, i.e., initial soil moisture and bulk density.~~ 3–9 datasets. The median error of the surface runoff was ~~44–46~~34–40% while that of the sediment ~~volume was 52–56~~mass was 41–49% (for the ORIG model these were ~~93 and 100~~78 and 95%, respectively). Errors below 100% characterised ~~78~~86% of the datasets for surface runoff and ~~70~~82% of the datasets for sediment ~~volume~~mass, whereas, for the ORIG model, these values were ~~50 and 42~~62 and 55%, respectively. ~~Table 5 statistically compares the model performance.~~ STEP1 was the best performing model for both the surface runoff and sediment ~~volume~~ mass prediction (as compared with ORIG in Figs. 4 and 5). ~~The simplest model~~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., ~~STRONG, produced better results for certain metrics than more complex models~~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 ~~similar error propagation values~~significantly better performance than the original approach, such that they can be used to predict the skinfactor. ~~The results suggest that the simplest function does not necessarily lead to the poorest result.~~

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 ~~six the~~ the six events using all of the transfer functions. Simulations with the skinfactor corrected by ~~-MAPE~~ MAPE to increase the infiltration rate, produced no runoff for all events. Only events 14.5. and

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	~~STEP3~~ STRONG
R^2	~~0.12~~ 0.14 ± 0.07	~~0.83~~ 0.85 ± 0.08	~~0.8~~ 0.83 ± 0.09	~~0.8~~ ~~0.79~~ 0.82 ± 0.09
RMSE	~~2.11~~ 2.09 ± 0.22	~~0.91~~ 0.88 ± 0.28	~~1~~ 0.97 ± 0.32	~~1~~ ~~1.02~~ 1.01 ± 0.31
RSR	~~0.94~~ 0.93 ± 0.03	~~0.41~~ 0.39 ± 0.11	~~0.45~~ 0.43 ± 0.11	~~0.45~~ ~~0.46~~ 0.45 ± 0.1
MAPE	~~1.92~~ 1.4 ± 0.52	~~0.72~~ 0.7 ± 0.25	~~0.66~~ 0.62 ± 0.21	~~0.67~~ 0.65 ± 0.24
MDAPE	~~0.7~~ 0.71 ± 0.19	0.3 ± 0.13	0.32 ± 0.08	0.34 ± 0.1
Intercept	~~−3.6498~~ −2.7909	~~−31.7377~~ −35.7264	~~−17.3803~~ −17.4628	~~−17.678~~ ~~−16.6319~~ −16.5647
Initial soil moisture	—	~~0.2845~~ 0.3195	~~0.1857~~ 0.1819	~~0.1711 0.1735~~ 0.1719
bulk density	—	~~0.0126~~ 0.012	~~0.0072~~ 0.0072	0.0074 ~~0.0074~~
silt	—	~~0.0847~~ 0.1499	~~0.0158~~ 0.0174	~~0.0195~~ —
vegetation cover	~~3×10^{-4}~~ -5×10^{-4}	~~—~~ 0.01	—	— ~~—~~
soil saturation- wet	~~1.5319~~ 1.5767	~~−1.864~~ −2.0971	~~−0.3461~~ −0.2851	— ~~—~~
soil texture class- sandy	~~−0.0761~~ −0.9513	~~20.7123~~ 24.4281	—	— ~~—~~
soil texture class- silty	~~0.4296~~ −0.4632	~~13.679~~ 17.8491	—	— ~~—~~
type of management practice- conventional tillage	~~−0.179~~ −0.2381	—	—	— ~~—~~
type of management practice- no tillage	~~−0.0256~~ 0.0098	—	—	— ~~—~~
type of crop- cereals	~~1.8503~~ 1.6397	—	—	— ~~—~~
type of crop- erosion permitting crop	~~1.3655~~ 1.4584	—	—	— ~~—~~

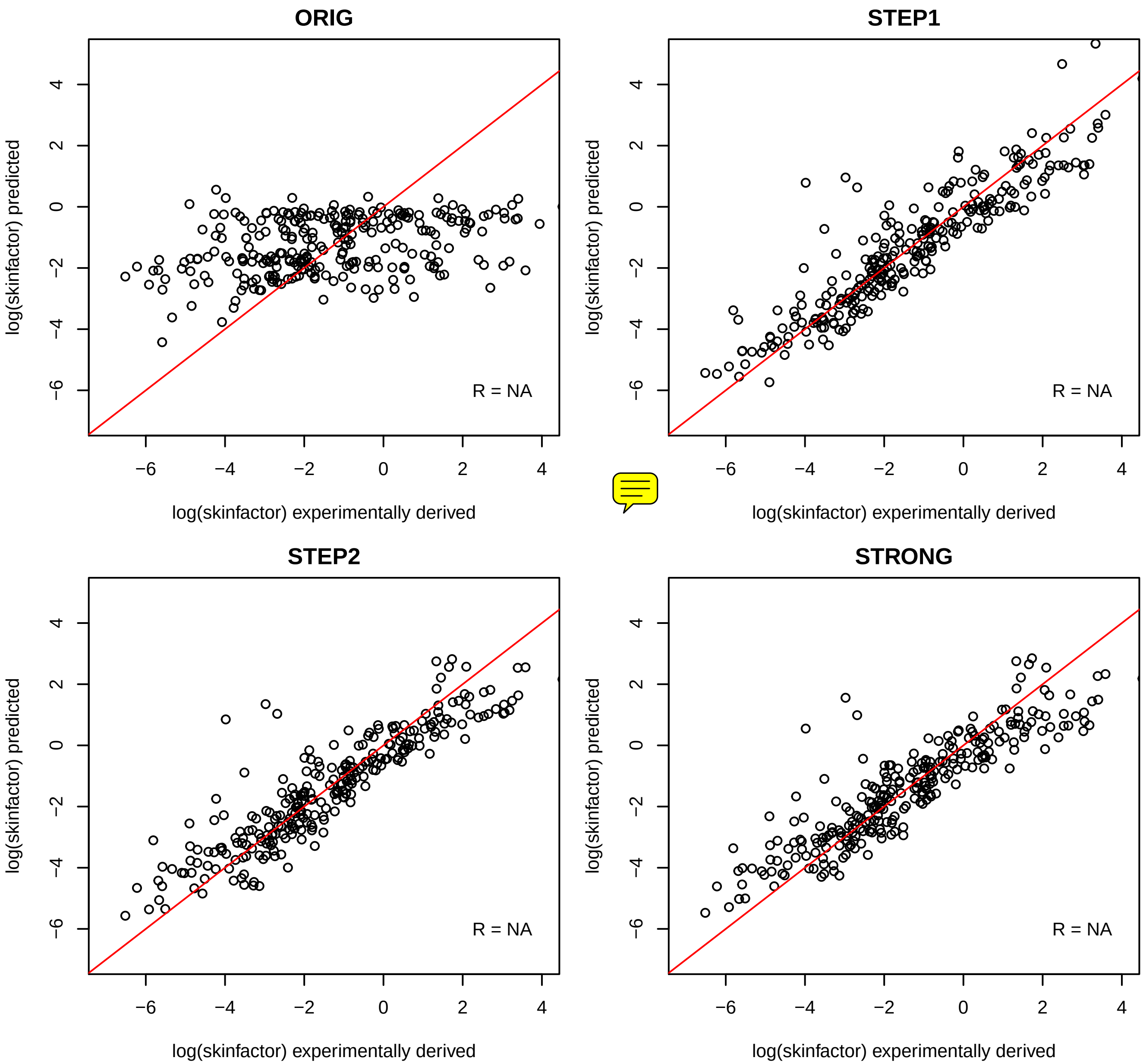

Figure 2. Experimentally derived versus predicted skinfactors (log values) for ~~the~~ selected validation dataset.

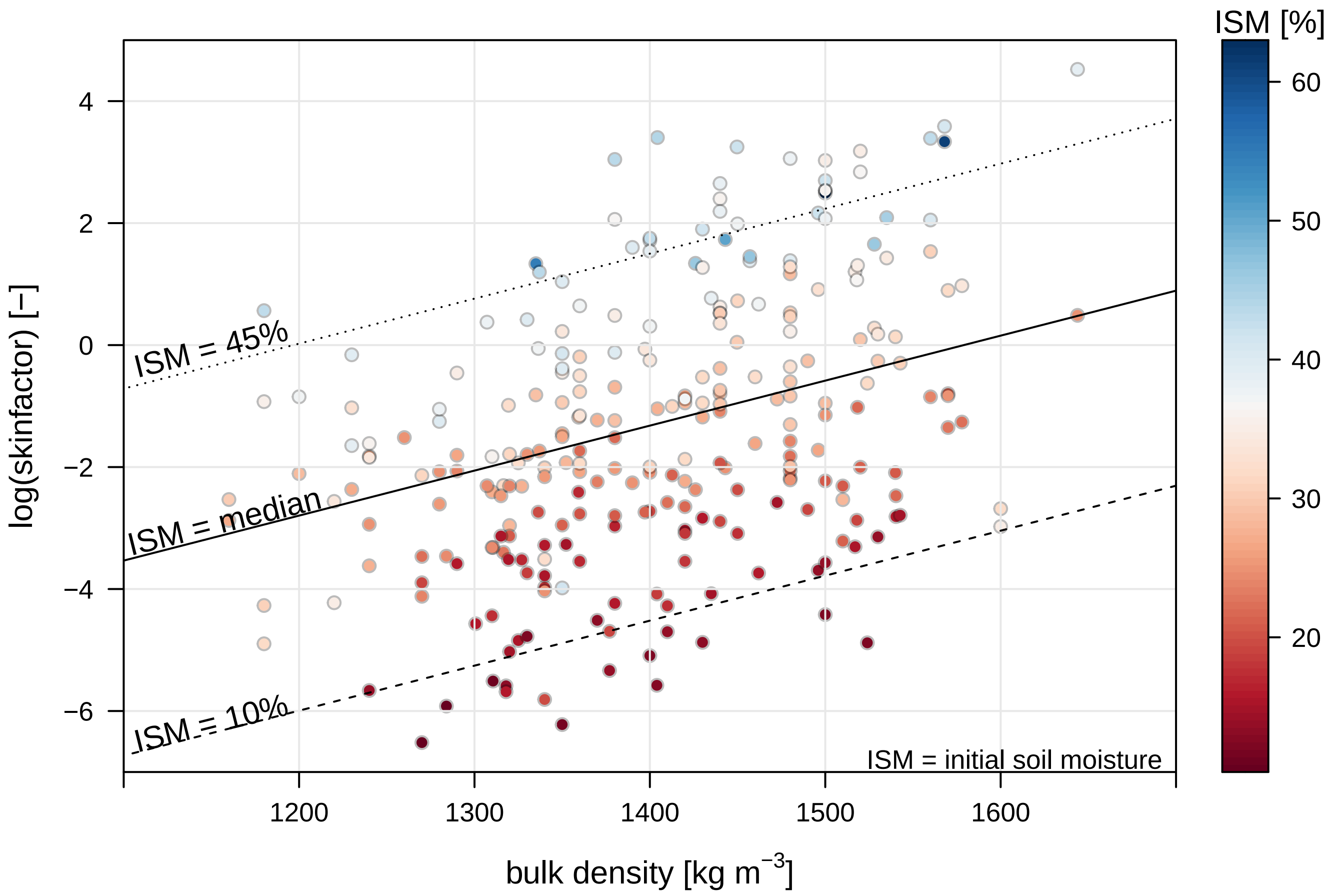

Figure 3. The dependency of the skinfactor on the bulk density and soil moisture. Point data represent whole dataset with experimentally derived skinfactors. Line data represent skinfactor prediction by STRONG for three different initial soil moisture conditions. ISM = initial soil moisture.

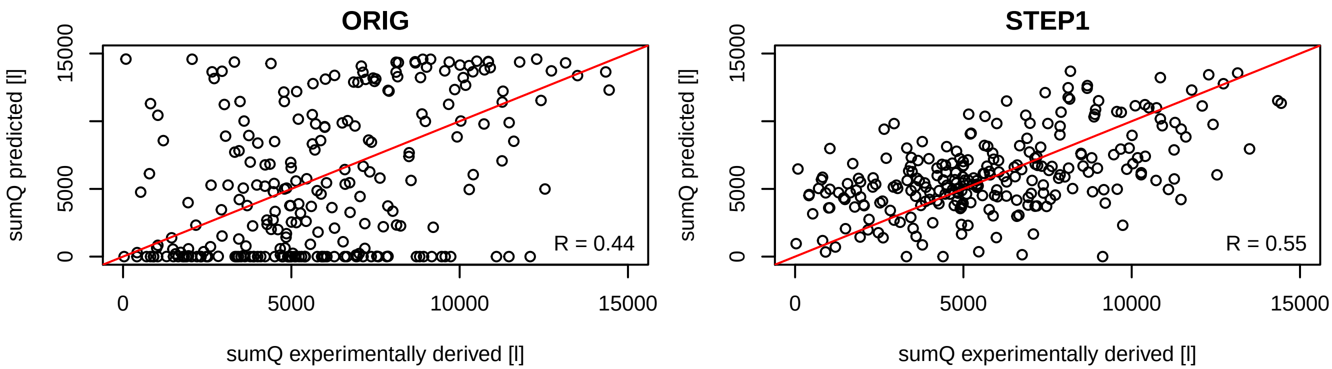

Figure 4. Surface runoff simulated with the derived skinfactor versus the ORIG skinfactor (left) and STEP1 skinfactor (right).

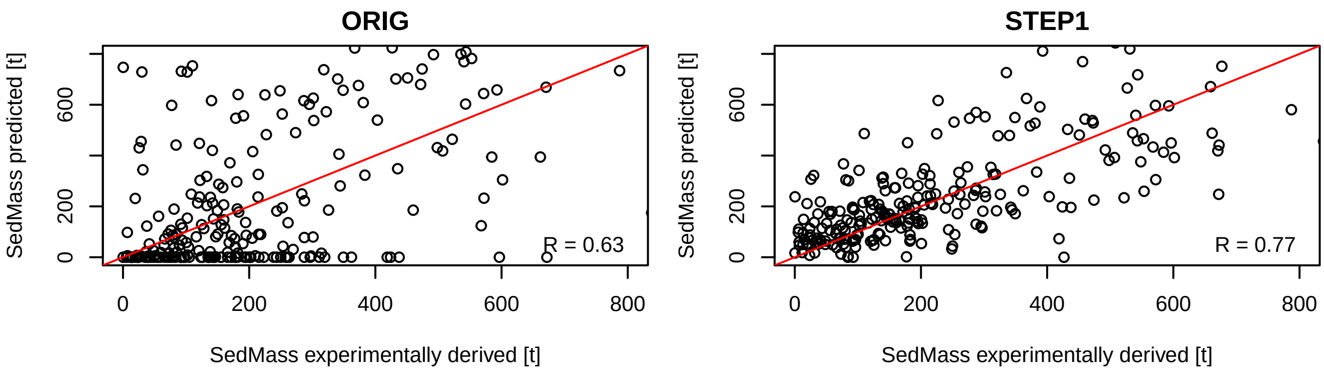

Figure 5. Sediment ~~volume~~ mass simulated by EROSION-3D with the experimentally derived skinfactor versus ~~the ORIG~~ skinfactor predicted by ORIG model (left) and STEP1 ~~skinfactor~~ model (right).

15.7. produced 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 ~~+MAPE correction~~ skinfactor decreased by MAPE produced runoff. The recorded runoff values for events 5.5., 2.7., and 11.7. are questionable, because the 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 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

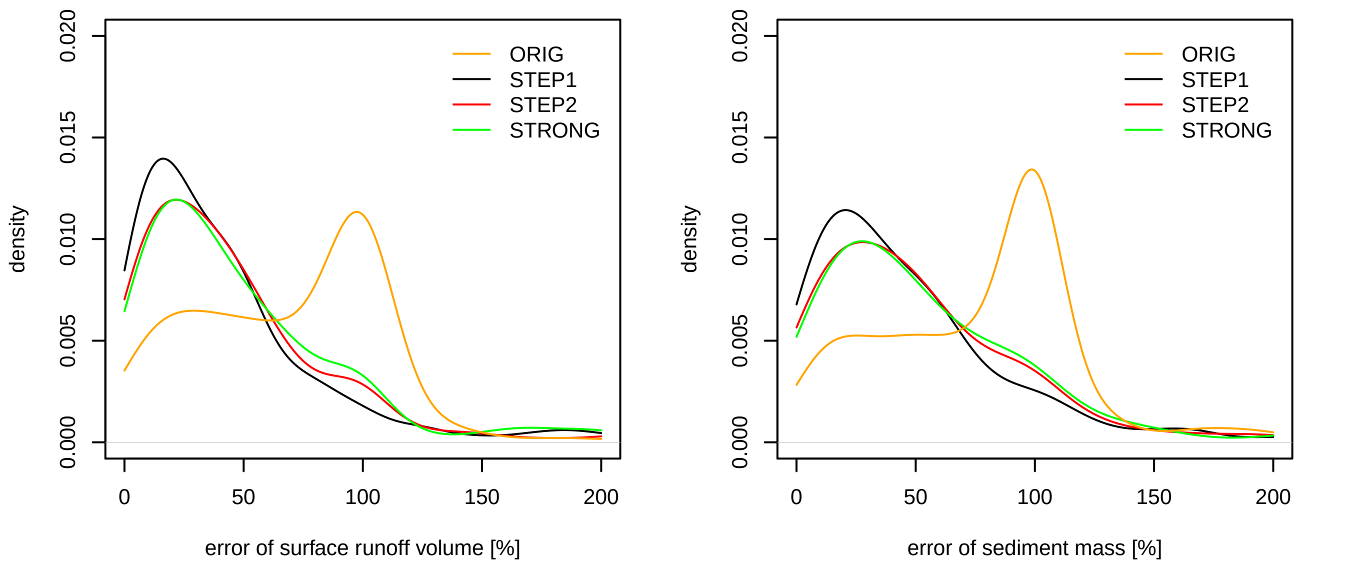

Figure 6. Error propagation ~~for~~ of skinfactor prediction in the surface runoff (left) and sediment ~~volume~~ mass (right), a density plot of the percent error. Outlying experiments (error > 200%) create 6–9% of the validation experiments. Experiments with no simulated runoff is evaluated as 100% error, which explains the significant peak in ORIG model.

the transfer functions. 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.

3.4 Discussion

The joint rainfall simulation dataset of TUBAF and RISWC provides a sufficient amount of data to statistically ~~analyse~~ analyze the relationships between the skinfactor calibration parameter and commonly measured soil and vegetation ~~parameters~~conditions, as well 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.

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 ~~this study show that the variables , except for the soil saturation have statistically negligible evidential~~ model ORIG show that out of these variables only soil saturation had statistically evident influence on the skinfactor. ~~The most~~

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

	ORIG	STEP1	STEP2	~~STEP3~~ STRONG
		surface runoff prediction		
no runoff simulated	~~24~~ 71	~~1~~ 3	~~2~~ 8	~~3~~ 9
outliers (error > 200%)	~~4~~ 14	~~5~~ 20	~~6~~ 24	~~6 5~~ 22
R^2	~~0.17~~ 0.19	~~0.23~~ 0.3	~~0.22~~ 0.2	~~0.23~~ 0.2
RMSE	~~5077~~ 4875	~~3077~~ 2840	~~3259~~ 3211	~~3311 3361~~ 3363
RSR	~~1.61~~ 1.58	~~0.98~~ 0.92	~~1.03~~ 1.04	~~1.05 1.07~~ 1.09
MDAPE*	~~0.93~~ 0.78	~~0.45~~ 0.34	~~0.44~~ 0.39	~~0.46 0.45~~0.4
		sediment mass prediction		
R^2	~~0.22~~ 0.4	~~0.46~~ 0.59	~~0.44~~ 0.51	~~0.42 0.47~~ 0.51
RMSE	~~288~~ 283	~~174~~ 161	~~184~~ 181	~~188 187~~ 196
RSR	~~1.24~~ 1.16	~~0.75~~ 0.66	~~0.79~~ 0.74	0.81 ~~0.8~~
MDAPE*	~~1~~ 0.95	~~0.52~~ 0.41	~~0.52~~ 0.48	~~0.53 0.56~~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	~~STEP3 sumQ~~ STRONG sumQ
14.05	0 - 100	0 / 13 / 122	0 / 13 / 115	0 / ~~33 / 145~~ 0 / ~~0 /~~ 83
15.07.	0 - 120	0 / 108 / 271	0 / 0 / 148	0 / 0 / ~~143 0 / 0 /~~ 22

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

~~significant predictors identified in this study, i.e., the initial soil moisture and bulk density, are highly variable in time and space and cannot be easily obtained. The initial soil moisture can be calculated from antecedent precipitation (Heggen, 2001) and other soil, vegetation, and relief properties (Pan et al., 2003; Zhao et al., 2011). Tramblay et al. (2011) used external software to derive initial soil moisture as an input parameter for the runoff model. The number of projects developing methods and producing open data for soil moisture based on remote sensing techniques is increasing (e.g., soil moisture CCI data by ESA (Gruber et al., 2019) and soil moisture active passive (SMAP)data by NASA (Enrekhabi et al., 2014)). Copernicus ERA5-Land provides soil moisture data produced by the combination of model data with observations from across the world (Copernicus Climate Chang Bulk density can be estimated by pedotransfer functions based on the soil texture and organic carbon content. Sevastas et al. (2018) presente a review and validation of 56 pedotransfer functions found in the literature. Another review of direct and indirect estimation methods for bulk density was presented by Al-Shammary et al. (2018). Global maps of bulk density at various resolutions developed within the SMAP project are available in Das (2013). Ballabio et al. (2016) presented the European map of bulk density.~~

~~The relationship between the skinfactor and the soil moisture and bulk density indicates that infiltration rates are overestimated at low soil moisture and low bulk density values and underestimated at high bulk density values by the infiltration module used in EROSION-2D/3D. Previous studies have also discussed the dependency on both the soil moisture and bulk density. Soil moisture has been explained by the~~ 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 explained by stability of aggregates (Michael, 2000). Dry aggregates are prone to destruction by enclosed air, which becomes compressed by water infiltrating into the aggregates. The smaller particles from the destroyed aggregates then cause surface sealing and smaller skinfactors. ~~Wet aggregates are more stable because their matrix potential is lower and the infiltrating water does not produce such high, destructive pressure in the aggregates~~

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 ~~is~~ 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~~, but are not considered in model algorithms. Therefore, all of these theories can be considered reasonable explanations for the dependency of the skinfactor on~~ . Our study indicates, that these theories explain only smaller part of the skinfactor 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, ~~but none of them are validated in the rainfall experiments. An alternative explanation is the misfit of the empirical estimation functions for the~~ which indicates drastic overestimation of infiltration 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~~and matrix potential. The experimental basis behind Campbell's model is unknown (Campbell, 1985).~~, 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 antecedent water content in EROSION-2D/3D and is calculated by equation 4. The ~~equations for the matrix potential estimation are based on the measurements of 40 important Belgian soil series. They represent a local dataset, which may be comparable to other regions, but validation is required (Vereecken, H. J., Maes, J., Feyen, J., and Darius, 1989). Schmidt (1996) showed that these equations lack accuracy for very dry conditions (pF >4).~~

~~The existing prediction methods for the skinfactor fail to include this dependency on soil moisture. They distinguish only between dry and wet run conditions (Michael et al., 1996; von Werner, 2009), which can rather correspond with the impact of the rainfall on soil cover (e. g., soil sealing and broken aggregates) as opposed to moisture (Fiener et al., 2011)~~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.

~~The dependency of the skinfactor on bulk density is associated with macropores and surface sealing (Michael, 2000). Soils with high bulk density values are likely treated with reduced tillage practice and therefore are rich on macropores, which enhance infiltration and lead to greater skinfactors. Soils with low bulk density are likely freshly ploughed and therefore are prone to surface sealing, which hinders infiltration and leads to lower skinfactors.~~

~~Previous studies associated skinfactor values greater than one with macropores and values smaller than one with surface sealing (Michael, 2000; Seidel, 2008; Schindewolf and Schmidt, 2012). This study indicates that skinfactor values do not systematically relate to these conditions; all of the experiments at dry conditions had skinfactors smaller than one, including those with reduced tillage, which tend to develop more macropores. However, this cannot be proven because surface sealing or macropore conditions were not recorded. Previous studies have attempted to determine the empirical equations for skinfactor prediction (Michael, 2000; Schlegel, 2012). Although these authors do not recommend the use of these equations (Schlegel, 2012), as well as the fact that certain predicted values are unreasonable (Lenz et al., 2018), the initial soil moisture and bulk density were identified as the most important predictors, which consistent with this study. In these attempts, experiments were grouped into subsets based on texture, management practices, and the type of run to derive regression models for the subsets. This method reduces the number of experiments and achieves higher values for each single subset, as compared with the method~~ To get better insight in the parameter fitting strategy Monte Carlo parameter optimization (Luengo et al., 2020) is tested, 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. Therefore 10000 randomly sampled combinations of the parameters are modelled with EROSION-3D. The parameter combination at which the RMSE of simulated and measured infiltration curve is the smallest represents the best found fit. The two methods are compared in Fig. 7. While the parameter

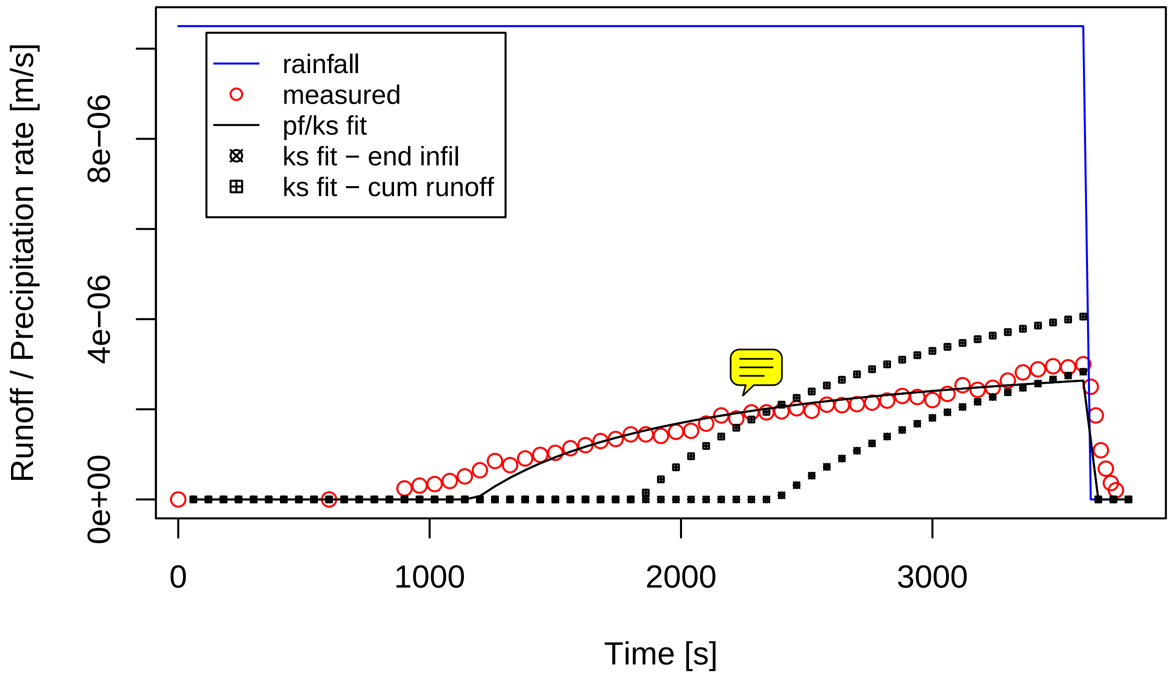

Figure 7. Comparison of parameter fitting strategies: ks fit refers to variation of hydraulic conductivity only (state-of-art in EROSION-3D) and pf/ks fit refers to best simulation found by Monte Carlo simulation.

optimization method is able to adequately simulate the infiltration curve in its whole extent, the single parameter method 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 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 Green-Ampt approach in EROSION-3D applied in this study ~~, which uses categorical variables as covariables in linear models. Previous studies determined different dependencies for the prediction parameters~~ can be seen as first step towards the use of advanced parameter optimization algorithms (e.g.~~, the intercept of soil moisture)on each single subset, whereas this study assumed an equal dependency on each parameter for the entire dataset~~ 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 ~~skinfactor calibration parameter~~ calibration parameter adjusting saturated hydraulic conductivity called skinfactor. The relationship of the skinfactor with soil, vegetation, and farm management parameters was analysed using 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 ~~79~~82% of the skinfactor variability. These parameters are not considered in currently available prediction methods provided in (Michael et al., 1996). Other significant predictors ~~of~~ such as soil texture (i.e., the silt content and KA5 soil texture group), vegetation cover and the impact of previous rain events ~~only~~ 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 ~~increases~~ increase in the skinfactor prediction accuracy, as compared with currently available methods (decrease in the ~~MAPE error from 192 to 66–72~~MDAPE error from 71 to 30–34%). Error propagation of the estimated skinfactors indicates substantial improvements to surface runoff and soil loss simulations. ~~Real rainfall-runoff events were modelled by EROSION-3D with the skinfactors predicted by the proposed functions, exhibiting good model performance for events with higher total precipitation and intensity.~~ The strong logarithmic relationship of skinfactor with soil moisture however indicates a suboptimal method of model parametrisation and 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 automatized 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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