Can the models keep up with the data? Possibilities of soil and soil surface assessment techniques in the context of process based soil erosion models – A Review

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Abstract. Climate change, accompanied by intensified extreme weather events, results in changes in intensity, frequency and magnitude of soil erosion. These unclear future developments make adaption and improvement of soil erosion modelling approaches all the more important. Hypothesizing that models cannot keep up with the data, this review gives an overview of 44 process based soil erosion models, their strengths and weaknesses and discusses their potential for further development

15   with respect to new and improved soil and soil erosion assessment techniques. We found valuable tools in areas, as remote sensing, tracing or machine learning, to gain temporal and spatial distributed high resolution parameterization and process descriptions which could lead to a more holistic modelling approach. Most process based models are so far not capable to implement cross-scale erosional processes or profit from the available resolution on a temporal and spatial scale. We conclude that models need further development regarding their process understanding, adaptability in respect to scale as well

20   as their parameterization and calibration. The challenge is the development of models which are able to simulate soil erosion processes as close to reality as possible, as user-friendly as possible and as complex as it needs to be.

1 Introduction

Soil, a natural resource with essential functions to the ecosystem, has experienced extensive degradation over the past
25 decades (Swinton et al., 2007; Evans et al., 2019). Soil degradation is caused by a combination of spatial and temporal
highly variable factors of natural and anthropogenic origin. Natural processes such as soil nutrient depletion, salinization and
soil erosion are intensified by anthropogenic influences, such as agricultural mismanagement, overgrazing, overexploitation
and environmental pollution (Jie et al., 2002; Baumgart et al., 2017). Soil erosion can lead to extensive soil loss and
eventually to the exposure of the underlying bedrock (Evans et al., 2019). Due to its complexity, the determination of
30 influencing parameters is challenging (Phinzi and Ngetar, 2019). Soil erosion represents a decisive process for degrading
agricultural land and with this crop yield on a global scale (Bakker et al., 2004; Zhang et al., 2004; Zhao et al., 2016).

Climate change, accompanied by an increase in frequency and magnitude of weather extremes, leads to spatially
differentiated changes in extent, intensity and frequency of soil erosion (Nearing et al., 2005; Routschek et al., 2014; Li and
Fang, 2016; Guo et al., 2019). A variety of studies such as Boardman et al. (1990), Favis-Mortlock and Boardman (1995),
35 Michael et al. (2005), Klik and Eitzinger (2010), Nunes et al. (2013) and Hu et al. (2020b) focusses on estimating climatic
impact on erosional processes. According to them, the impact of climate change on soil erosion varies greatly depending on
the region. One approach to better estimate these impacts, suggests to link climate change models with soil erosion models
working on a high temporal resolution (Li and Fang, 2016).

Climate change having its direct impact on soil erosion, also triggers indirect drivers, such as anthropogenic activity, changes
40 in crop management or land use changes, which can affect soil erosion even more strongly (Li and Fang, 2016; Guo et al.,
2019). While soil erosion on arable land is generally higher than on non-arable land (Cerdan et al., 2010), it largely depends
on land management practices. Consequently, adapted land management is an important step towards the sustainable use of
soils (Mullan et al., 2012; Routschek et al., 2014). The protection and conservation of soils has become a major social
challenge worldwide and represents an important field of research (Govers et al., 2007). To support soil protection efforts
45 and recovery strategies, precise assessments of erosion rates and information on erosion and sedimentation processes are of
crucial importance (Boardman and Poesen, 2006; Evans et al., 2019).

Research on this topic started early in the last century, with first modelling approaches in the 1940s by Zingg (1940) (quoted
in Wischmeier and Smith, 1965) and the development of an empirical based soil erosion model, the universal soil-loss
equation (USLE) by Wischmeier and Smith (1965). Since then many soil erosion and sedimentation models have been
50 developed and many authors have reviewed them, providing an overview of the variety of existing models. Amongst others,
they point out the following limiting factors for process based soil erosion models:

- High data demand and model complexity (Pandey et al., 2016)
- The risk of equifinality (Govers, 2010; Batista et al., 2019)
- Temporal unchanging soil and surface input parameters (Merritt et al., 2003; Pandey et al., 2016)
55 - Spatial homogenous soil input parameters for areas of similar properties (Pandey et al., 2016; Merritt et al., 2003)
- Scarce data availability (Schindewolf et al., 2013)
- Only a selective process description (e.g. leaving out gully erosion, rill-interill interaction or rill initiation) (Aksoy
  and Kavvas, 2005; Hajigholizadeh et al., 2018)

For a more holistic understanding of soil erosion and an impact reduction by applying adapted management strategies,
60 models need to integrate the current understanding of soil erosion processes from splash to gully erosion (Parsons, 2019; Li
and Fang, 2016). The continuous development and improvement of measurement techniques for soil erosion and soil
properties, lead to spatially and temporally highly resolved information at different scales (Li et al., 2017). In this context, it
is of great interest to consider how far they can contribute to the improvement and further development of soil erosion

models. Based on these considerations we work with the hypothesis that models cannot keep up with the data, in the context

65   of which, we consider the

    i)   State-of-the-art

-    Are current process based soil erosion models insufficient in terms of parameterization and modern process description at high spatial and temporal scales?

-    What are the opportunities and limitations offered by today's data assessment techniques?

70   ii)   What to do next?

-    Can today's potential in data assessment overcome shortcomings and improve existing models?

-    Can soil erosion process descriptions be delineated from modern erosion measurement techniques and be integrated into the models?

-    Can these data possibilities make the models more accurate and improve them in terms of parameterization and

75   validation?

This review intends to offer scientists an overview of potentials and shortcomings of process based soil erosion models, especially regarding their capabilities of implementing data from new and improved measurement techniques. Along this interface, we want to identify the relevant factors for verification and advancement of these models based on today's possibilities of data generation and processing to overcome limitations and to improve soil erosion modelling.

2 Soil erosion assessment – state of research

Today, a large number of soil erosion models exist and a wide range of methods for measuring soil erosion processes by

145   water have been developed. A brief summary on process based soil erosion models is provided, taking the spatial and temporal frame, the limitations, capabilities and the type of considered erosion process, into account. An overview of soil erosion assessment techniques follows, focusing on their type of assessment and the temporal and spatial scale they can be applied to.

2.1 Process based soil erosion models

150   Models as simplifications of reality can, by definition never represent the processes of the real world in its entirety. Soil erosion modelling started with the development of first empirical based models in the middle of the last century (Wischmeier and Smith, 1965; Wischmeier and Smith, 1978; Renard et al., 1991) and where, with the improvement of computing power and data availability, followed by process based or physically based soil erosion models (Schmidt, 1991; De Roo and Offermans, 1995). The latter, while being more complex regarding their input data, computing requirement, calibration

155   necessity and being less user-friendly, offer due to physical based descriptions of soil erosion and sediment transport a more accurate understanding and reproduction of the occurring processes (Hajigholizadeh et al., 2018). Process based models therefor enable a better extrapolation and transferability of the results than empirical based models (Merritt et al., 2003; Lane et al., 2001; Li et al., 2017; Pandey et al., 2016; Vente et al., 2013; Schindewolf et al., 2013). Furthermore, they allow an isolated consideration of individual components of soil erosion processes as well as a better understanding of the relationship

160   between cause and impact within soil erosion research (Scherer, 2008).

Soil erosion models can be further distinguished along different aspects, as their considered temporal (continual/event-based) and spatial (field/catchment/regional) scale, or their distribution of erosion patterns (lumped/spatially distributed) (Karydas et al., 2012). Water erosion, as a discontinuous process, is mainly driven by single extreme rainfall events (Edwards and Owens, 1991), making the event-based simulation an important aspect. Spatially distributed models enable spatially

165   distributed predictions, as ranking erosion prone areas, sediment dynamics within a catchment and acceptable simulations of outlet transport rates (Batista et al., 2021).
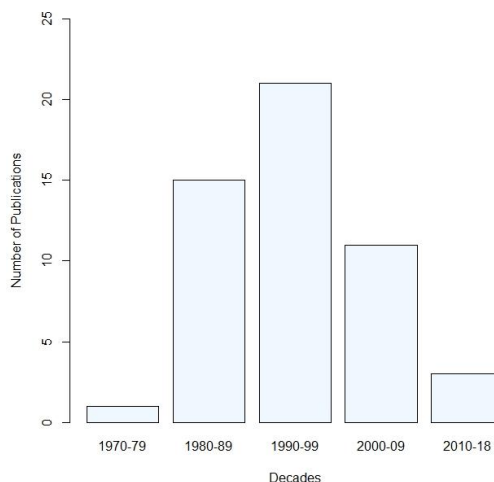
Figure 1: Development decades of process based soil erosion models based on Aksoy and Kavvas, 2005: 253), Karydas et al., 2012: 10), Hajigholizadeh et al., 2018: 11-13), Merritt et al., 2003: 766, 791) and Pandey et al., 2016: 600-606).

170 Considering that many process based soil erosion models have been developed in the end of the 20th century (fig. 1), the question arises which of the once limiting factors might be outdated and can be remedied with the help of new measurement techniques and temporal and spatial high resolution data as well as new possibilities regarding processing and computing power. Taking different perspectives into account, several authors have reviewed soil erosion models in recent years (Merritt et al., 2003; Aksoy and Kavvas, 2005; Jetten and Favis-Mortlock, 2006; Pandey et al., 2016; Hajigholizadeh et al., 2018;

175 Guo et al., 2019; Baartman et al., 2020), considering the following aspects:

- Possibilities and limitations regarding the user
- Model requirements
- Input data
- Process representation
180 - Spatial and temporal resolution
- Output data
- Model strengths and weaknesses
- Influencing variables
- Fundamental equations
185 - Future development ideas
- Regional fit
- The representation of connectivity

Based on five review papers on soil erosion models published between 2005 and 2018, tab. 1 offers a selection of process based soil erosion models focusing on the similarities and differences of 44 models, their capabilities regarding process

190 descriptions as well as their limitations.

Table 1: Process based soil erosion models compiled according to Aksoy and Kavvas, 2005: 253), Karydas et al., 2012: 10), Hajigholizadeh et al., 2018: 11-13), Merritt et al., 2003: 766, 791) and Pandey et al., 2016: 600-606), with information on the temporal scale (E = event based/ C = continuous), the spatial distribution (L = lumped/ D = distributed), the spatial scale (F = field, W = watershed/catchment), their integration of Geographic Information Systems (GIS) and an overview of their processes and
195 **capabilities as well as their limitations and missing aspects (gully erosion = GE, rainfall runoff = RR, in-stream sediment = InS, overland sediment = OS, sediment associated chemicals =SAC)**

Model information	Spatial & Temporal Scale & Distribution			Processes/Capabilities	Limitations/Missings
	E/C	F/W	L/D		
ARMSED (Riggins et al., 1989)	E	W	-	RR; generation, transport & deposition of OS; runoff peak discharge; runoff volume	GE, SAC; high data demand
AGNPS[1] (Young et al., 1989) (Ann) AGNPS[2] (Bingner and Theurer, 2001)	E[1] C[2]	W	-	RR; sediment transport; SAC; daily time step[2]	sediment deposition, sediment connectivity; poor for large watersheds due to heterogenic input data; only single event[1]; GIS (medium)
ANSWERS[1] (Beasley et al., 1980) ANSWERS continuous[2]	E[1] C[2]	F W	D	RR; generation, transport & deposition of OS; channel erosion; spatial variation in soil infiltration capacity[2]	GE; SAC; rill structure; sub-surface flow; only transport by runoff; high data demand; erodibility as time constant parameter; GIS (medium)
CASC2D (Julien and Saghafian, 1991), CASC2D-SED[2] (Johnson et al., 2000)	E C	W	D	Generation, transport and deposition of OS and InS; suited for urban and agricultural watershed	Rill structure; sub-surface flow; reservoir flow; channel sediment; GE; SAC; GIS (low), high data demand[2]
CHILD (Tucker et al., 2001)	E	F W	D	RR; gully formation; generation, transport & deposition of InS	SAC; poor sedigraphs simulation; high data demand
CREAMS (Knisel, 1980)	E	F	L	RR; GE and deposition; SAC; rill structure; sediment yield; peak flow; percolation to groundwater; generation, transport and deposition of OS	InS; GIS (low); uniform in soil topography and land use; high dependency on accuracy of input data; assumption of homogeneity; high data demand
CESP (Kirkby and Cox, 1995)	E	W	-	RR; GE; generation, transport and deposition of OS and InS	SAC; high data demand
DWSM (Borah et al., 2004)	E	W	D	GE; SAC/flood agrochemical transport; generation, transport and deposition of OS and InS; surface and underground runoff	GIS (medium); long computing time; low robustness; high data demand
EGEM (Woodward, 1999)	E	F	D	Ephemeral GE; hillslope sediment	SAC; RR; generation, transport and deposition of OS and InS; moderate data demand
EPIC[1] (Williams et al., 1984) GEPIC[2] (Liu et al., 2007)	E	F	L	Hillslope sediment; surface runoff; percolation; subsurface flow; wind and water erosion; nutrients and pesticides; GIS-based[2]	GE; GIS (low)[1]; processes limited to small scales
EROSION2D/3D (Schmidt, 1991; Werner, 1995)	E	F W	D	RR; generation, transport and deposition of OS and InS; suitable for large scale simulations	GE; high computational effort; high data demand
EUROSEM (Morgan et al., 1998)	E	F	D	Erosion, transport and deposition by rill and interrill processes; splash erosion before runoff; total runoff; total soil loss; storm hydrographs and sedigraphs	GE; RR; SAC; bank collapse in channel, crusting algorithm; poor with dynamic data and vegetated surface; high data demand; cannot generate rills
EUROWISE (Torri & Morgan 1998	E	W	-	RR; GE; sediment yield	SAC

Model				Description	Notes
GLEAMS (Knisel and Turtola, 2000)	E C	F	L	RR; SAC; generation, transport and deposition of OS; pesticides and plant nutrients; user-friendly; effects of agricultural management practices on water quality	GE; generation, transport and deposition of InS; high data demand; GIS (low)
GSSHA (Downer and Ogden, 2004)	E C	W	D	GE; RR; generation of OS and InS; underground runoff; raindrop impact	SAC; sub-surface flow
GUEST (Misra and Rose, 1996)	E	F	D	RR; generation, transport and deposition of OS; sheet erosion; rill erosion	GE, SAC; GIS (low); high data demand
HEM (Lane et al., 1995)	E	F	-	RR; SAC; generation, transport and deposition of OS and InS	GE; high data demand
KINEROS[1] (Woolhiser et al., 1990) KINEROS2[2] (Goodrich et al., 2002)	E	W	D	Generation, transport and deposition of OS; peak rate; RR[2]; channel sediment; GIS (high); splash erosion[2]; rill erosion[2]	RR; GE; SAC; sub-surface flow; high data demand
LISEM[1] (De Roo et al., 1994) OpenLISEM[2]	E	W	D	RR; SAC; rill structure; sediment and storage depression; variable time intervals; spatial distribution of soil erosion and deposition; GIS (high); generation of OS; generation, transport & deposition of InS; soil crust; GE; transport capacity; settling velocity	Ephemeral GE; high data demand (detailed spatial representation required); sediment sources and deposition processes not correctly simulated; most sensitive variable: saturated hydraulic conductivity
MEFIDIS (Nunes et al., 2006)	E	W	D	RR; peak runoff; erosion (based on extreme rainfall events)	Chemical simulation; GIS (low)
MIKE11 (Hanley et al., 1998)	E C	W	-	RR; SAC; generation, transport and deposition of InS; GIS (high); sediment and water quality; cohesive and non-cohesive sediments; large complex catchments with varying land use, soil and management	GE; bank erosion; OS; high data demand; 1-D equation to represent 3-D processes
MIKE SHE (Abbott et al., 1986)	E	F W	-	RR; generation, transport and deposition of OS and InS	GE, SAC; GIS (loose); high data demand
MWISED (Torri et al., 2002)	E	F	-	RR; gully formation; transport of OS; generation, transport & deposition of InS	SAC; high data demand
OPUS (Smith, 1992)	E	F	D	RR; SAC; GIS (high); generation, transport & deposition of OS	GE; high data demand
PEPP (PEPP-Hillflow) (Schramm, 1994)	E	F	D	RR; SAC; generation, transport & deposition of OS and InS and phosphorus; preferential flow in macro-pores	GE; GIS (medium); high data demand
PERFECT (Littleboy et al., 1992)	E	F	L	RR; SAC; crop yield	GE; high data demand (crop and tillage); GIS (low); field to small catchment; calibration (NE Australia)
PESERA (Kirkby et al., 2004)	E C	W	L	RR; generation, transport & deposition of OS; crop growth; GIS (high)	GE; chemical simulation & flow routing not fully developed; regional to national scale
REGEM (Gordon, 2006)	E	W	-	Gully formation; RR; SAC; generation, transport and deposition of OS and InS	High data demand
RillGROW (Favis-Mortlock, 1998)	E	F	D	Spatial development and location of rill system	Field scale; GIS (low); range lands
RUNOFF (Borah, 1989)	E	W	D	RR; peak rate; GIS (high); low data demand; generation, transport and deposition of OS; rainfall detachment	GE; SAC; rill structure; parameters fixed in time
SEM (Storm and Jorgensen, 1987)	C	W	D	Generation, transport & deposition of OS and InS; splash detachment	GE; RR; SAC; high data demand
SEMMED (Jong et al., 1999)	C	W	-	GE; RR; generation, transport and deposition of OS	SAC

SHE[1]/SHESE D[2] (Abbott et al., 1986)	E[1] C E[2]	F W	D	RR; GIS (high); subsurface hydrology; generation, transport and deposition of OS	GE; SAC; rill structure; bank erosion; frozen soil erosion; high data demand
SHETRAN (Bathurst et al., 1996)	E	F W	D	RR; SAC; peak runoff rate; GIS (high); generation, transport and deposition of OS and InS	GE; no flow simulation through unsaturated zones
SIMWE (Mitas and Mitasova, 1998)	E	W	-	RR; GE; generation, transport & deposition of OS	SAC; data demand high
SMODERP, SMODERP2D (Dostál et al., 2000)	E	F W	D	Effective precipitation; RR; stream network routing; surface retention	GE
SPNM (Williams, 1980)	E	F W	-	RR; SAC; generation, transport and deposition of InS	GE
SWAT/SWAT-WB (White et al., 2011)	E C	W	D	RR; SAC; sediment yield; GIS (high)	GE; flood peaks; snow melt runoff
SWRRB (Williams et al., 1985)	E C	W	L	SAC; RR; subsurface flow; sediment yield	GE; high data demand
TOPMODEL (Beven and Kirkby, 1979)	E C	W	D	RR; subsurface runoff; sediment yield; GIS (high); low level of expertise necessary	SAC; GE; suitable for shallow homogenous soil; long dry periods and moderate topography
TOPOG (O'Loughlin, 1986)	E	W	D	RR; SAC; erosion hazard; splash erosion; generation, transport and deposition of OS	GE; SAC; high data demand; GIS (moderate)
WATEM[1]/ SEDEM[2] (van Oost et al., 2000)	C	F[1] W[2]	D	Generation, transport and deposition of OS and InS; tillage erosion; sedimentation rate; low data demand; limited input data; user-friendly	GE, RR, SAC, river channel erosion; GIS (moderate)
WEPP[1] (Laflen et al., 1991) GeoWEPP[2] (Renschler et al., 2002)	E C	F W	D	Generation, transport & deposition of OS and InS; RR; raindrop detachment; GIS (high)[2]	GE, SAC, rill structure; high data demand; large computational demand
WESP (Lopez-Garcia and Caselles, 1987)	E	W	D	Generation, transport & deposition of OS and InS; RR	GE, SAC, rill structure; lack of information on erosion and deposition parameters; poor simulation of sedigraph; GIS (moderate)

While process based models exist, which are more frequently used than others (e.g. LISEM), researchers continue to develop
200 soil erosion models, to create approaches that have advantages in one or the other way (e.g. being more accurate to simulate a specific process or being more simplified) (Hajigholizadeh et al., 2018). As models are conceptualized for different purposes as well as spatial and temporal scales (Karydas et al., 2012), they vary widely regarding their complexity, data demand, temporal and spatial representation of process mapping as well as input and output parameters (Pandey et al., 2016). As simplifications of reality, the all-achieving model does not exist jet, which results in a constantly rising and meanwhile
205 confusing amount of models with a range of different strengths and weaknesses, as listed in tab. 1.

In their study on 16 European erosion models Jetten and Favis-Mortlock (2006) review them next to others with respect to their process representation. They emphasize the problem, that different models are calibrated for special spatial and temporal scales, and in general assume continuous temporal soil and surface input parameters, which lead to falsified process description. The models e.g. EGEM, EPIC, GLEAMS, GUEST or PERFECT are developed to simulate erosion on the field
210 to small catchment scale. Restrictions such as these are often accompanied by the practical aspect of data availability (Pandey et al., 2016), a factor with decreasing importance due to the increasing possibility of collecting high resolution data on a large spatial and temporal scale. Aksoy and Kavvas (2005) see further potential of model improvement amongst others

in implementing the process description of rill-interrill interaction in soil erosion models. Various models, e.g. ANSWERS, WEPP, PERFECT, LISEM, EUROSEM or KINEROS2, lack the ability to simulate gully erosion processes, making the application in large gully prone areas unfeasible (Hajigholizadeh et al., 2018). The prediction quality of a model is heavily influenced by its input data and its parameterization, which concludes appropriate data collection from multiple sources, accurate model parameterization and temporal and spatial high resolution input data as important aspects for model improvement (Batista et al., 2021; Pandey et al., 2016).

2.2 Techniques on soil erosion measurement

Measurement techniques to assess soil properties and soil erosion are constantly advancing in terms of their spatial and temporal resolution (Li et al., 2017). In the context of reviewing those, most researchers focus on a selection of similar technological approaches but do not take a holistic overview on assessment techniques into account (e.g. Padarian et al., 2020; Castillo et al., 2012). Li et al. (2017) i.e. compare the selected methods of runoff plot, radionuclide tracers and erosion pins for soil erosion assessment. Taking just a few methods into account, they predict a future trend towards merging different methods for more quantitative and precise approaches. Rodrigo-Comino (2018), includes 91 publications in his review on soil erosion assessment methods. To gain an improved understanding of processes and connectivity, he as well recommends a combined application of methods, working on different temporal and spatial scales. Figure 2 gives an overview of assessment techniques used in soil erosion research, compiled according to types of assessment and ordered by their applicability on a temporal scale.
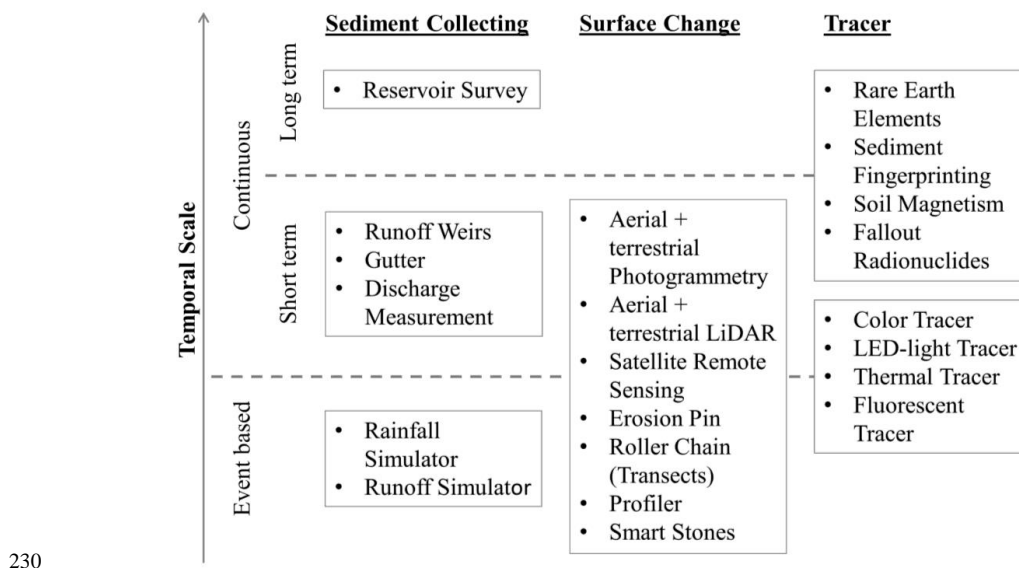
Figure 2: Soil erosion assessment techniques, for further information please refer to: Guan et al. (2017), Li et al. (2017), Jester and Klik (2005), Thomsen et al. (2015), Batista et al. (2019), Rodrigo-Comino (2018) (LiDAR = Light Detection and Ranging).

2.2.1 Tracer

Authors as Guzmán et al. (2013) and Guan et al. (2017) review different tracing approaches, as also listed in fig. 2 – namely the fallout radionuclides of both anthropogenic and natural origin as e.g. Caesium-137 (^{137}Cs), Beryllium-7 (^{7}Be) or Lead-210 (^{210}Pb$_{ex)}$. These tracers are capable of reconstructing sedimentation histories on different temporal scales, from a few months up to approximately 100 years (Mabit et al., 2008; Alewell et al., 2017; Guan et al., 2017). While ^{137}Cs is most suitable for the measurement of medium-term soil erosion on slope scales (Baumgart et al., 2017), combining soil erosion modelling with both ^{7}Be and soil measurements can help to improve the understanding of soil relocation processes

240   (Deumlich et al., 2017). Joining [7]Be with high resolution unmanned aerial vehicle (UAV) photogrammetry shows useful to quantitative assess surface change detection in a spectrum of up to 2 mm resolution (Baumgart et al., 2017), offering high resolution cross-scale measurement of different erosion processes. Rare earth elements, which can be of natural origin or artificially added, are useful for studying both rill and interill detachment and deposition processes from the plot up to the catchment scale. Using the magnetic properties of the soil, natural or artificially incorporated, magnetic tracers enable the

245   reconstruction of sediment sources on different temporal and spatial scales. Sediment fingerprinting takes the chemical, biological or physical properties of soil into account, comparing a given composition at one area with those elsewhere (Guan et al., 2017; Guzmán et al., 2013). Combining different tracing and soil erosion monitoring approaches on different temporal and nested spatial scales, can be used to identify sediment sources, and their change of spatial and temporal distribution in a catchment over time (Guan et al., 2017).

250   To better understand the influence of spatial variability in water erosion, Guzmán et al. (2013) see big potential in the use of magnetic tracers and spectroscopic techniques. Regarding the last one, Alexakis et al. (2019) present, with the opportunities artificial neural networks offer us today, a time as well as cost efficient way to monitor soil parameter using spectroscopy by satellite data. They describe the opportunity for fast and efficient ways of parameter assessment on a large scale. With the development and improvement of sensor systems, capable tracing methods arise, measuring with high accuracy e.g. the for

255   soil erosion crucial flow velocity. Next to colour dyes, fluorescent dyes, fluorescent particles or electrolytes, such an approach is the thermal tracing (Lima et al., 2015; Tauro and Grimaldi, 2016). Thanks to an increase in resolution, portability and a reduction in cost, today infrared thermography offers a fast, effective and accurate opportunity to monitor flow velocity via thermal tracer on a high temporal and spatial resolution (Lima et al., 2015; Lin et al., 2018).

2.2.2 Remote Sensing

260   While remote sensing shows already useful in combination with tracing approaches, it can also stand alone as a valuable tool in soil erosion and soil property assessment. In this context, satellite sensors provide a vast range of spatial resolutions, spectral bands and revisiting times. They show great potential for soil erosion measurements due to the method's robustness, the large spatial scales and the data availability especially in remote regions, they furthermore are becoming affordable and display low time expenditure of data assessment (Sepuru and Dube, 2018). Data by e.g. Sentinel 1, Sentinel 2 or Landsat 8

265   offer a great spectrum of information on i.e. soil organic carbon, soil total nitrogen, clay content of the soil or the Normalized Difference Vegetation Index (NDVI), with resolutions up to 10 m (Septianugraha et al., 2019; Zhou et al., 2020; Gholizadeh et al., 2018). While valuable to identify erosion and its consequences on the medium to large scale (Vrieling, 2006) and showing usefulness for empirical models working on large areas (Aiello et al., 2015), satellite data has not yet established itself in combination with process based soil erosion models, mostly used on smaller, slope to catchment, scales.

270   Methods on aerial and terrestrial photogrammetry and aerial and terrestrial LiDAR or laser scanning (ALS and TLS) are very valuable in soil erosion research and become even more efficient with further development and improvement in computing power (Guo et al., 2016; Neugirg et al., 2015; Glendell et al., 2017). They allow, remote sensing with high temporal and spatial resolution. The photogrammetric technique Structure from Motion (SfM) via UAV offers a powerful and achievable method for measuring soil erosion, also in terrain difficult to access (Neugirg et al., 2015). Thanks to their high spatial and

275   temporal resolution, photogrammetry and LiDAR can be used to measure on-going soil erosion processes quasi continuous during artificial and natural rainfall events. On the one hand the data can be used to e.g. validate measured soil loss on an artificial plot while on the other hand they give valuable insight on the continuous process of soil erosion (Guo et al., 2016; Hänsel et al., 2016). Yang et al. (2021) offer a spatial high resolution monitoring of the development of rill and interrill erosion via TLS and SfM (with resolutions less than 1 mm) on an artificial plot (0.7 m²), concluding for SfM a high accuracy

280   in quantifying rill erosion. On an even smaller scale Laburda et al. (2021) use SfM to monitor splash erosion, working on resolutions of up to 0.1 mm. Low cost, terrestrial, high resolution photogrammetry enables surface change detection in the

sub-minute time step and with sub-millimetre resolutions, offering new insight in detailed soil erosion processes from the micro perspective (Kou et al., 2021).

UAVs equipped with cameras, as a cost-effective and flexible tool (Pineux et al., 2017), offer the assessment of spatially
285   distributed soil surface changes over different temporal and spatial scales and with resolutions in the low millimetre range (Kaiser et al., 2018). These datasets and the quantification of soil loss help to assess and understand the water erosion mechanisms and the spatial and temporal dimension of the soil erosion processes taking place on the slope to catchment scale (Cândido et al., 2020; Eltner et al., 2018). LiDAR, despite the higher time and cost expenditure, proves a feasible tool for change detection (Li et al., 2020a), helping to improve the understanding of soil erosion forms, as soil crusts (Hu et al.,
290   2020a) or rill characteristics (Vinci et al., 2015). Jiang et al. (2020) monitor rilling on an artificial plot via LiDAR and SfM. They promote the use of close range photogrammetry, achieving even higher accuracies than by the use of TLS. Meinen and Robinson (2020) see great potential in UAV SfM-MVS (multi-view stereo) for validation and calibration of soil erosion models. Photogrammetric approaches and LiDAR, allow a spatial and temporal high resolution cross-scale understanding of on-going processes and their development from the microplot to the catchment scale, offering cross-scale validation
295   opportunities and new and accurate process understanding by water induced soil erosion to process based soil erosion models.

Hu et al. (2020a) use LiDAR to quantify results of interrill erosion processes. They describe LiDAR as a promising technology for generating microtopography soil parameters, which can be linked to high resolution photogrammetric derived Digital Elevation Model (DEM). Photogrammetry and TLS as non-invasive, high accuracy, high mobility and in the case of
300   photogrammetry low cost techniques allow the assessment of soil properties as e.g. roughness (Thomsen et al., 2015; Kaiser et al., 2018; Li et al., 2020b; Gilliot et al., 2017) or soil moisture (Kemppinen et al., 2018). Soil spectra measured via remote sensing are an important step for in-situ assessment of soil properties at real time (Ge et al., 2011). Remote sensing enables the spatially distributed assessment of soil properties on a high temporal resolution, which can be of great value for the parameterization of physically based soil erosion models. Thomsen et al. (2015) already point out that the possibilities
305   offered by SfM and TLS regarding the survey of roughness exceed the integration opportunities of process based soil erosion models such as LISEM. This supports the hypothesis that the models cannot keep up with the available data and that the latter need to be further developed for an appropriate inclusion of the novel possibilities.

2.2.3 Machine Learning

Machine learning (ML) approaches as artificial neural networks (ANN) offer cost and time efficient ways for spatially
310   distributed assessment of soil parameters (Alexakis et al., 2019) and erosion forms, as e.g. gully erosion (Arabameri et al., 2020a; Arabameri et al., 2020b). Different authors have used different ML approaches to map the susceptibility of gully erosion and the factors controlling it (Lei et al., 2020; Pourghasemi et al., 2020). In this context Pourghasemi et al. (2020) found the Random Forest approach the most reliable to understand such controlling factors. While techniques have been developed to use ML (e.g. linear equation model or decision tree) based on visual data to predict soil properties (i.e. soil bulk
315   density), those approaches seem only to be applicable for approximate in situ measurements, filling the gaps of laboratory assessed data (Bondi et al., 2018). Deep learning, as ANN can offer new opportunities to model soil spectral data (Padarian et al., 2019). Open source algorithms combined with proximally and remotely assessed soil data enable the use of ML approaches to analyse soil data (Padarian et al., 2020). While there is great potential in ML approaches for soil erosion prediction and management (Vu Dinh et al., 2021), there also exists the risk of equifinality, gaining plausible results for the
320   wrong reason (Padarian et al., 2020). While these techniques offer new possibilities they so far show most useful on regional scales with large data availability (Zhang et al., 2018b) and up to now have not found their way in improving process based soil erosion models.

3 Challenges and opportunities of process based soil erosion modelling in the context of novel data acquisition methods

325 Limits set by computing power are constantly shifting and creating new possibilities. In addition, the required time and cost for the collection of high resolution data is decreasing and new opportunities arise. In the development of soil erosion monitoring, measuring approaches have become more precise and thus small scale monitoring techniques were supplemented by those applicable to large, regional scales (Li et al., 2017). Due to improved and novel assessment technologies, possibilities for process based soil erosion models constantly increase. In the following the necessity for model

330 adaption and further development, regarding the aspects of parameterization and calibration, process description, scale and resolution as well as complexity and equifinality will be discussed.

3.1 Parameterization and calibration

Being time and resource consuming and accompanied by a high parameterization requirement, expecting input parameters on e.g. topographic data, soil data, tillage practices and crop management, process based soil erosion models, are considered

335 rather complex, making them more difficult in their handling than empirical models (Merritt et al., 2003; Pandey et al., 2016; Hajigholizadeh et al., 2018). To reduce assessment time and complexity and to increase user-friendliness, the input parameters are often assumed homogeneously distributed for the whole field or catchment (e.g. CREAMS). Nether the less new assessment techniques especially in the field of remote sensing can extremely facilitate the procurement of highly resolved parameters on both temporal and spatial scales, enabling distributed input data in both time and space (Eltner et al.,

340 2018; Jester and Klik, 2005; Kaiser et al., 2015). Time-varying input data for process based models as the RUNOFF model, are important to gain more accurate results (Aksoy and Kavvas, 2005), while also their flexibility in space proves to be of great value (Guo et al., 2019).

Even parameters such as roughness, which over the past, for the lack of other possibilities, were determined empirically, can increasingly be derived, by remote sensing, as shown for the models LISEM (Thomsen et al., 2015) or EROSION3D (Kaiser

345 et al., 2015). Due to its high resolution, SfM enables the spatially distributed assessment of roughness on a large scale (Eltner et al., 2018). Besides novel methods in the field of topographic reconstruction and ML, advances in the area of image velocimetry as mentioned before, bare great potential for an automatic measurement technique, offering new possibilities for the parameterization of process based soil erosion models (Lima et al., 2015; Lin et al., 2018).

Since they represent reality in a simplified way, models cannot include all influencing factors. Model developers therefore

350 decide to include certain processes as close to reality as possible and to neglect others in order to avoid overly complex models. This results in a large number of models with different strengths and weaknesses. Regarding the precipitation, there are models, as EROSION3D, taking the temporally variable intensity of the rainfall event into account (Pandey et al., 2016) while others, e.g. PERFECT, ignore this impact using the same intensity for every time step (Merritt et al., 2003). An aspect widely neglected by process based models is the influence of wind-driven rain on soil erosion. This influence of the wind

355 can be immense with up to 30 % more erosion, emphasizing the need for assessing and integrating high resolution data on near surface wind speed and direction in soil erosion modelling (Marzen et al., 2017; Schmidt et al., 2017). Recent advances in time-lapse SfM photogrammetry allow for the assessment of surface changes during a rainfall event with a temporal resolution of several seconds (Eltner et al., 2017). Such data, combined with surface wind speed and direction, can offer new possibilities for the further development of process based soil erosion models. While up to a certain degree, the model's

360 accuracy improves with the number of input parameters, in general more input parameters lead to an increasing model complexity. A balancing act of process based models is the over-parameterization: the more parameters are included in a model, the greater the risk of having a stochastically fitting model that however fails to map the processes actually taking place (Pandey et al., 2016; Vente et al., 2013; Jetten et al., 2003).

In the case that parameters cannot be assessed directly, the calibration of the models helps to determine these parameters and

365 thus to achieve the best possible agreement between measured and modelled output (Merritt et al., 2003; Pandey et al., 2016). One or multiple parameters are calibrated against an available dataset to minimize the prediction error (Batista et al., 2019). While Guo et al. (2019) see improvement in generating more extensive calibration data for soil erosion models (e.g. MEFIDIS), regarding the GSSHA model Pandey et al. (2016) on the other hand propose, less dependency on model calibration all together. Based on high resolution data, a better process understanding can help reduce the necessity of model

370 calibration. Further model development as improving the parameter validation and calibration for models e.g. SHETRAN, MEFIDIS, GLEAMS and WESP can already help reduce the risk of equifinality – gaining a statistical right answer for the wrong reason (Guo et al., 2019; Batista et al., 2019; Pandey et al., 2016).

3.2 Soil erosion processes

The soil erosion processes, as splash, interrill, rill and gully erosion, show high variability in their process description

375 (Batista et al., 2019) and are represented differently well depending on the model. Models as ANSWERS miss the sediment transport by rainfall (splash erosion) (Hajigholizadeh et al., 2018), while others such as EUROSEM simulate splash erosion, but only until interrill erosion starts (Aksoy and Kavvas, 2005). Different soil erosion models are developed for different scales and therefore vary regarding their process description (Batista et al., 2019). Models for small scales depict splash erosion and interrill erosion especially well, where there are models developed for larger scales, focusing on gully erosion.

380 Due to the complexity of the occurring and transforming soil erosion processes, many models make simplified assumptions. The KINEROS model for example does not differentiate between interrill and rill erosion (Aksoy and Kavvas, 2005), while WEPP simulates interrill erosion and concentrated runoff within rills, but does not take the transition from one to another into account (Merritt et al., 2003).

While most process based soil erosion models are capable of modelling runoff and soil erosion within existing rills as well as

385 in interrill areas, they miss the ability to depict spontaneous rill formation (Pandey et al., 2016). Existing rill erosion models, such as RillGROW 2 by Favis-Mortlock et al. (2000), can map the hydraulic processes inside a rill, but are unable to model its initiation (Wirtz et al., 2010; Pandey et al., 2016). An approach on a WEPP-based soil erosion model by Wu et al. (2018) simulates erosion and rill evolution on the hillslope scale. However even this model is not capable to model every occurring rill formation and has difficulties in locating the bifurcation and merging of rills. The embedding of the initiation and

390 development of rills in soil erosion models is an important future step to gain more precise modelling results (Wu and Chen, 2020).

To this goal, a new and improved process understanding, gained by repeated and accurate rill erosion assessment (Di Stefano et al., 2017) and detailed information about their origin, geometry and frequency (Merritt et al., 2003) is an important step in the understanding and modelling of rills. Advances in time-lapse SfM photogrammetry allow for the assessment of surface

395 changes during a rainfall event with a temporal resolution of several seconds (Eltner et al., 2017). Such approaches, as well as information gained by rare earth elements on rill-interrill erosion processes, might enable an enhanced temporal and spatial high resolution process understanding (Zhang et al., 2018a). Information that can help develop and integrate a topographic threshold concept, as suggested by Nouwakpo et al. (2016) to implement the transition from interrill to rill erosion in process based soil erosion models. Different assessment techniques offer opportunities for an enhanced

400 understanding of soil erosion processes and especially the cross-scale transition from one process to another.

Gully erosion as an important driver of land degradation is in many cases neglected by process based soil erosion models (Pandey et al., 2016; Lei et al., 2020). There are certain landscapes, as the loess plateau in China or areas in Iran, where annual sediment loss due to gully erosion exceeds that of slope erosion by far, making it a severe environmental problem (Cai et al., 2019; Arabameri et al., 2020b). For these gully-prone areas, as well as for cross-scale and large scale soil erosion

405 modelling the incorporation of gully erosion processes in process based soil erosion models is of great importance (Li and

Fang, 2016; Cai et al., 2019). Various ML approaches are used for the susceptibility mapping of gully erosion (Arabameri et al., 2020a), which could be a helpful extension for the detection of gully initiation in process based models.

Often unattended by these models, is the simulation of nutrients and chemical paths as shown by the models: AGNPS (Adu and Kumarasamy, 2018), CASCA2D, DWSM, EGEM, EROSION2D/3D, KINEROS, MEFIDIS, PERFECT, PERSERA,
410 RUNOFF, SHESED, WATEM or the WEPP (Pandey et al., 2016). Nether the less as soil erosion is to great parts an agricultural challenge such discharge presents an important modelling aspect (Tao et al., 2020). For a better understanding of soil relocation processes, including nutrients and chemical paths, and to implement them in soil erosion models, Deumlich et al. (2017) propose to combine soil erosion models, with the tracer technique [7]Be as well as soil measurements.

Considering that changing climate leads to an increase in extreme weather events, it is important to gain a holistic
415 understanding of processes and feedback mechanisms (Vereecken et al., 2016; Guo et al., 2019). Guo et al. (2019) recommend to implement such aspects and to further develop soil erosion models in respect to changing climate scenarios. Bringing together knowledge of different disciplines Li and Fang (2016) propose combining climate, land use and soil erosion models to achieve a both multi-scenario as well as multi-model framework for an improved simulation of soil erosion influenced by climate change, associated land use changes and adopted management strategies.

420 **3.3 Scale and resolution**

Process based soil erosion models deliver the best results in the observation scale they were parameterized and validated for (Batista et al., 2019; Govers, 2010; Hajigholizadeh et al., 2018; Cerdà et al., 2013; Vente et al., 2013). The governing equations are usually derived on the basis of small scales and then transferred to larger scales, which can lead to poor validation results (Hajigholizadeh et al., 2018). Most models are developed for the field scale (e.g. GUEST or RillGROW),
425 the field and small catchment scale (e.g. CREAMS, EGEM, EPIC, EROSION3D, EUROSEM, GLEAMS, OPUS, PEPP-HILLFLOW, PERFECT and WATEM) or the catchment scale (e.g. TOPMODEL) (Pandey et al., 2016). By changing the considered scale, both prevailing erosional process as well as the complexity of these processes alter (Govers, 2010; Merritt et al., 2003). Taking the role of scale into account is important to understand the dominant processes and their influence on erosional rates (Vente and Poesen, 2005). With improving technology, large scale, high resolution data is available, enabling
430 a validated extension of the spatial modelling scales (Baartman et al., 2020).

To gain reliable and accurate results, the resolution and quality of the different input data is of importance to the model performance (Merritt et al., 2003; Alewell et al., 2019). The impact of the cell size on the soil erosion simulation varies with the model choice. The LISEM model for example proves more adaptable to changes in spatial and temporal resolution than EROSION3D, where the choice for the right solution shows to be more complex and requires a higher modelling experience
435 (Starkloff and Stolte, 2014). Varying the DEM cell size in either direction, can lead to a different focus on operating processes and connectivity (Baartman et al., 2020). Due to new and further developed assessment techniques, data with higher temporal and spatial resolution arise, offering new opportunities and challenges for modelling approaches. Changes in resolution can lead to changes in the representation of hydrology or topography and therefore affect soil erosion predictions (Zhang et al., 2008; Cochrane and Flanagan, 2005). An increasing resolution can expose non-erosive processes, as e.g.
440 swelling and shrinking, which may mask the actual erosional processes (Kaiser et al., 2018). Therefore an holistic understanding of soil erosion processes, including its scale, is inevitable (Cerdà et al., 2013). Remote sensing data can enable temporal and spatial high resolution change detection and process mapping on different magnitudes (Balaguer-Puig et al., 2018; Cândido et al., 2020), offering such information for soil erosion modelling.

3.4 Model complexity and equifinality

445 One downside of process based compared to empirical soil erosion models is the model complexity. Nether the less, there are little to no alternatives if the model is to be transferable and offer spatially differentiated and event-based predictions

(Hessel et al., 2006). Complex models are not automatically the better choice (Jetten et al., 2003). An increase in complexity is not necessarily reflected in improved modelling (Govers, 2010), but enhances the dependency of modelling results on the modeller's experience (Merritt et al., 2003). With rising complexity process based models forfeit user-friendliness (Batista et al., 2019). Model development therefore is a balancing act between complex models that represent reality as accurate as possible and user-friendly models developed for a wide range of users.

The large number of input data not only results in a high model complexity but also in a large number of degrees of freedom (Govers, 2010). Varying parameter combinations can lead to equally sufficient model outputs (Batista et al., 2019), misjudging the relationship between observed and predicted erosion (Evans and Brazier, 2005). Even though the model adequately simulates the sediment yield at the systems outlet, it not necessarily implicates a correct process description or a correct spatial distribution of erosion and deposition (Starkloff et al., 2018). This points out another challenge of process based soil erosion models, the risk of achieving the correct outcome for the wrong reasons (Govers, 2010). Even though the model is working poorly in identifying spatially distributed erosion hotspots or representing internal dynamics it might still offer a realistic prediction of the overall simulation outcome in respect to soil loss and runoff at the systems outlet (Favis-Mortlock, 2010; van Oost et al., 2005). Modellers should be aware that equifinality is an inevitable consequence of model calibration (Batista et al., 2019), which might even lead to misdirected management and recovery strategies (van Oost et al., 2005). Spatially and temporally distributed data, as high-resolution surface change detection, can be used for validation and thus help reducing the risk of equifinality.

3.5 Connectivity

The complexity and multitude of processes taking place within a catchment, affects the sediment and water transfer throughout the system. To address management strategies and mitigation measurements, it is inevitable to gain a holistic overview of the system's connectivity, shifting the perspective away from the single slope to the connected system and taking a variety of spatial scales into account. Such knowledge leads to a better understanding of the influences of human built structures and natural landforms on the continuity of water and sediment transfer throughout the system as well as the cause of off-site damages (Cavalli et al., 2019; Biddulph et al., 2017). Models, being simplifications of reality, often neglect the delayed reaction of the sediment yield and the impact of sediment connectivity (Vente et al., 2013). Supplementary to erosion rate assessment, the mapping and modelling of sediment transport and runoff throughout the system, is of major importance as it has great influence on off-site damage (Boardman et al., 2019). Regarding accurate modelling results the aspects of sediment sources and connectivity might be even more important than the model parameterization (Uber et al., 2020).

High rainfall intensity leads to large amounts of sediment yield, which increases the impact of connectivity. Stronger events result in better simulated sediment connectivity (Baartman et al., 2020). Including connectivity analysis into soil erosion models, the parameterization of the landscape and rainfall characteristics are decisive (Uber et al., 2020). For a best-fit of sediment transfer to its outlet, Mahoney et al. (2020) stress the need of coupling erosion, sediment routing and connectivity formula. The GeoWEPP-C model, based on the GeoWEPP, offers an approach of integrating process based soil erosion modelling and modelling of lateral sediment connectivity. While this model presents an opportunity to combine these different aspects, it still needs major improvement before applicable to the practice (Poeppl et al., 2019). To gain insights on the development of connectivity on short to long terms Baartman et al. (2020) propose a continuous monitoring and modelling of runoff and sediment transfer. GIS-based indices offer an approach to overcome the extensive field work and large amount of input data necessary to partly quantify relevant connectivity factors (Najafi et al., 2021). Even though connectivity is up to now just to some extents assessable, new high resolution remote sensing data (e.g. DEMs), help measuring connectivity aspects at least partway and enable the development of connectivity indices (Heckmann et al., 2018), which can be of interest to process based soil erosion modelling.

4 Conclusion and outlook

490 Climate change accompanied by local changes in extreme weather events, as droughts, rising temperature, high rainstorm intensity and temporal precipitation shifts also leads to changes in soil erosion rates. A major influence on soil erosion in modern times is human-driven land use changes. Unclear future developments only make an adaption of assessment techniques and modelling approaches all the more important. Regarding heavy local rainstorm events, resulting in intensified local soil erosion, assessment and modelling on the sub-daily scale is of great importance (Mullan et al., 2012). This review

495 gives an overview of 44 process based soil erosion models, their strengths and their shortcomings. Potential of their further development is based on new opportunities, which assessment techniques offer the soil erosion research today.

Hypothesizing, that models cannot keep up with the data, we found several weaknesses that can be improved or even eliminated, utilizing up to date assessment techniques of soil erosion research. Future research should focus on incorporating improved, new as well as spatial distributed input data and an updated process description. Evaluating the scale dependent

500 boundaries of processes, researchers should strive to include the initial development of rills and enable cross-scale modelling from the micro-plot to the regional scale. Huge potential could be found by remote sensing, to further develop process descriptions, assess parameters as topography, roughness or flow velocity with high temporal and spatial resolution, or to work across scale. Techniques, with low cost, low time expenditure and high resolution, show potential to gain adequate data from the micro to the macro scale. Further of interest are ML approaches and tracing techniques. They for once pave the way

505 to respond to different processes on different scales (splash-, sheet-, rill-, gully erosion, transport and deposition). ML and automated assessment systems, could even offer opportunities on a completely new level, enabling the development of fully automated modelling approaches in the future.

Over the years many soil erosion models have been developed, resulting today in a large amount of process based models with different strengths and weaknesses. Even though the models are not capable to include the different erosional processes

510 or make use of the newly available resolution or temporal and spatial scale, the question arises if we need jet another model or if we could further develop and improve existing approaches. These models should be adapted to our possibilities and needs, to meet the current data availability and achieve a more holistic process understanding. The goal should be to achieve a realistic but user-friendly model, minimizing challenges as equifinality and offering an improved understanding of soil erosion processes and influences.

515 **Authors contribution**

L. Epple conceptualized and prepared the manuscript with supervision of A. Eltner and A. Kaiser and the reviewing and editing from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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