Towards climate-smart sustainable management of agricultural soils

SCALE

Managing Sediment Connectivity in Agricultural Landscapes for reducing water Erosion impacts

Deliverable WP3-D3

Catalogue on data sets to be used on different scales and models

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1 Introduction

Soil erosion models differ in their parameterisation and process simulation depending on the scale they were developed for. Often simplified assumptions are made to describe the complex soil erosion and sediment transport processes. It is thus important to use the right model at the right scale and feed it with appropriate data for the intended modelling scenario. Further, datasets needed for calibration and validation of the model outcomes are crucial for the validity of the results and their potential impact on the implementation of targeted mitigation measures.

Thus, the aim of this deliverable is to compile a catalogue that assists model users to select suitable datasets appropriate for their respective modelling approach and intended spatio-temporal scale.

When gathering needed data sets for a modelling scenario, it is firstly important to identify the problem and define the scope of the modelled scenario and the processes within. It is fundamental whether the scenario is focused on erosion hotspot identification, connectivity issues or the implementation of mitigation measures as these different scenarios may require different data sets. Model selection depends on both the modelling scenario, but can also be influenced by the data availability within the study area. Throughout the modelling, it is also important to recognise that all data sets have some inherent uncertainties and that data quality affects the outcome and interpretation of the model results. Furthermore, data is needed for calibration and validation of the model as well.

The choice of data set and which data are needed also very much depends on the scale of modelling and its purpose.

The application of soil erosion models at a very local scale such as **field scale** rather serves the investigation into detailed erosion and deposition processes. For example, sheet, rill and gully erosion can be distinguished and modelled individually. Changes in these erosion processes can be simulated for single rainfall events at high spatial resolutions. Spatial variability in land cover (vegetation density, stones) and connectivity elements such as tracks or ditches can be incorporated. Field scale modelling can further assist local planning purposes such as the design and effect of implementation of specific mitigation measures, e.g. against "design storms" with a certain occurrence. The model application should thus be adapted to the individual study area and locally measured data of high resolution is necessary.

Catchment scale modelling efforts are often applied for soil erosion management scenarios, to aid land use planning and assess erosion/deposition risk throughout the catchment area over continuous time scales. Runoff and sediment transport throughout the catchment can be modelled, introducing a greater need to include data on possible connectivity elements. Depending on the applied spatial resolution of the study area and input data, catchment scale modelling may allow for inclusion of the diversity of the landscape while still representing it explicitly (small-scale catchment). In larger catchments, only larger features may be explicitly modelled (others may be applied as factors affecting erosion) and erosion processes and spatial variability in land cover may be averaged. For soil-related model parameters, the use of pedotransfer functions (PTFs) or literature might become necessary, due to unavailability of specific maps for many model parameter values.

At **regional/national scale** erosion processes are averaged into homogenous spatial units such as grid cells or hydrologic units. The total soil detachment and sediment transport can then be expressed for each of these units within the study area. Often field parcels are used as the final units

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in risk assessment maps to show the average pattern of erosion risk as well as erosion hotspots, and where mitigation measures could be implemented. The assessment is often performed for long-term time scales. Mitigation measures and connectivity elements at this scale will likely be represented as e.g. a percentage of the surface area that increase or reduce erosion and sediment transport, instead of explicit features due to a too coarse resolution. At regional/national scale comparability of model results becomes particularly important in the context of policy-relevant erosion risk maps such as those supporting joint policies like the CAP. In these scenarios, harmonisation of data sets could be valuable to achieve a fair implementation of mitigation measures domestically (Plambeck, 2020; Schmaltz et al., 2024).

Here we present an overview of criteria to consider and possible datasets for each of these scales and for certain soil erosion models and their model parameters.

2 Dataset catalogue

Table 1 presents possible datasets for each of the input parameter categories rainfall, soil, topography, land cover and management and conservation practices, which most models require. Each of the RUSLE factors, which also cover these mentioned parameters, are also stated. On EU-level a lot of data has been collected which is openly accessible. For example, European-wide data have been published by the European Commission's Joint Research Centre (JRC) for the model RUSLE. As the datasets used for the EU-wide RUSLE factor calculations are often based on data collected in each EU-country, these datasets may also be relevant at regional/national level and are given as examples in Table 1. However, the application for the chosen research area should be investigated, as some controversy towards their validity in specific regions has been discussed (Auerswald et al., 2015). Regional/national data are often available within each country in their national INSPIRE database. However, many regional/national datasets may exist but they might not all be freely accessible and may have to be collected from several different sources. Field scale data is often collected through direct measurements within the study area. A mix of these different data sources are often used for catchment studies, depending on the catchment size and aim of the model application. Field or catchment scale measurement data are likely harder to obtain, as these data often lie in the hands of specific institutions and may not be publicly accessible.

In Table 2, data needed for (process-based) model-specific parameters are stated. These data can usually still be acquired without model calibration. The included process-based models build on the work in work package 4 of the SCALE project, so includes examples of relevant parameters, but it is not an exhaustive list.

Data for more advanced and experimental parameters e.g. those parameters that users have to parameterise themselves have been included in Table 3. These data are usually only obtainable by model calibration, and measurements of the model outputs are typically needed.

While the first two categories of input data are usually easy to obtain and make the model also applicable for a wider public, like practitioners or landowners, the third category can be limited to dedicated research or model development activities. An aspirational goal of model development should be to move as many "advanced" parameters into the other categories.

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Table 1. Basic data that most models need (factors from the RUSLE model).

Parameter	Scale and datasets		
	Field	**Catchment**	**Regional/National**
Rainfall (R-factor)	Locally based rainfall data needed, e.g. rain gauge or disdrometer. High temporal resolution (1-5 min) needed if event-based calculations are foreseen for e.g. for erosion process studies or mitigation measure scenario modelling. The use of disdrometer data allows for direct kinetic energy estimation and the use of empirical kinetic energy-intensity relationships can be omitted. Temperature data may be needed to filter out days with snowfall from the rainfall erosivity calculations. Other climate data may be needed by more process-based models for plant-growth simulations (see Table 2).	Rainfall data covering the extent of the catchment needed, e.g. several rain gauges in the area or spatially distributed R-factor for large catchments. High temporal resolution is preferable (5-10 min).	Long-term rainfall data (normally >20 years) needed to calculate a spatially distributed R-factor. Calculated based on rain gauge data with different kinds of interpolation methods (e.g. Hanel et al., 2016; Johannsen et al., 2022; Meusburger et al., 2012) or radar data (Auerswald et al., 2019). High temporal resolution is still preferable. Examples of using a single value as representative for a large regional area exist e.g. in Flanders, Belgium (Swerts et al.,2019). Other studies (e.g. Räsänen et al., 2023) use the spatially distributed R-factor calculated on European-wide basis for their country. <u>Possible datasets:</u> European-wide R-factor based on REDES database with rain gauge stations from the EU countries (Panagos et al., 2015a).
Soil data - particle size distribution, org. mat. content, soil structure, permeability, aggregate stability (K-factor)	Soil data from sampling at the site is highly relevant. Very high spatial resolution can be reached with the following techniques: LiDAR, photogrammetry, gamma-ray spectroscopy. Temporal variability of soil erodibility might be considered at this scale.	Soil sampling data interpolated between sampling sites or soil maps, geostatistical interpolation methods, or pedotransfer functions can be considered.	Often soil erodibility (K-factor) maps or values based on soil types or texture classes may exist (e.g. based on soil maps). Satellite data can be used for digital soil mapping. K-factor is often considered temporally static at this resolution. <u>Possible datasets:</u> EU-wide LUCAS topsoil dataset also used for the K-factor estimations for the whole of EU (Panagos et al., 2014). European Soil Database SoilGrids

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Topography - Digital elevation data, slope orientation, slope length, slope steepness (LS-factor)	DEM should be high resolution to be able to model the small-scale processes. Can be achieved via LiDAR, local UAV laser scanning and photogrammetry, which are high-resolution spatial and temporally distributed input data. Resolutions < 1 cm are possible, but not necessarily feasible.	DEM based on LiDAR data, Airborne laser scanning (ALS) or photogrammetry. Temporal distribution is often limited.	High resolution DEMs often exist nationally. Important to consider the correct resolution for the applied modelling scenario, as the DEM resolution can affect the soil erosion estimation. Regional or national ALS campaigns resulting in DEMs with 1-10 m resolution. Temporal resolution even more limited. Regional or national-scale LiDAR campaigns might be decades apart or a singular occurrence. Satellite data with much coarser resolution (ASTER GDEM, SRTM, EU-DEM (>30m)) might be available but are likely insufficient for typical agricultural conditions in Europe, especially when considering connectivity elements. Similarly, digitized topographical maps can be used for lack of better data. <u>Possible datasets:</u> EU-wide LS-factor in 25 or 100 m resolution (Panagos et al., 2015b).
Land cover and management (C-factor)	Detailed management information (machinery, tillage depth, crop residues, fertilization, actual crop development, yields); plant growth model	Land Parcel Identification System (LPIS) data contains georeferenced agricultural field blocks (polygons) identified and digitized from mainly ortho-imagery, which are potentially eligible for EU aid application. Sentinel data (several relationships approaches) NDVI-based.	Literature C-factor values can simply be attributed to land use maps without further land sub-classification. Satellite data for canopy and residue surface cover, and vegetation-based indices for spatiotemporally described land use classifications in remote sensing approaches. <u>Possible datasets:</u> CORINE land cover - a pan-European inventory with 44 thematic classes for specific reference years (latest 2018). European C-factor Dataset at 100 m resolution for arable and non-arable land with account of certain management practices for the reference year 2010 (Panagos et al., 2015c).

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Conservation practices (P-factor)	Detailed management information and details of how potential conservation practices affect erosion processes e.g. observed effectiveness from field studies. Within RUSLE, P values obtained from experimental data supplemented by analytical experiments are listed. However, the effectiveness may vary greatly, and it is recommended to adapt P-values for specific field conditions.	Implicit representations (just adding new reference value to represent a conservation practice, assuming homogeneous behaviour) or explicit representation with actual spatial heterogeneity preserved – each method requires different input data.	Inventories of support practices may exist in the national records of aid being paid for implementation of agri-environmental schemes (IACS). Literature values on the effect of support practices from experimental studies. Possible datasets: Support practices factor (P-factor) at European scale in 1 km resolution for reference years 2010 and 2016 (Panagos et al., 2015d). Partly based on the LUCAS dataset of stone walls and grass margins.

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Table 2. Model-specific parameters/input data. Literature references either indicate the mentioned dataset or method directly, or are exemplary applications in case studies. Parameters indicated by an asterisk (*) are shared by more than 2 models.

Parameter	Scale and datasets			Model
	Field	**Catchment**	**Regional/National**	
Tillage direction	Visual field inspection shows the tillage direction and seems superior to any data-driven method for a small number of fields	Visual inspection of orthophotos or high-resolution satellite imagery seem practical at small catchment scales; if not possible, the methods for regional/national scale can be applied	For large spatial scales, tillage direction can be estimated from field geometry (typically the direction of the longer side), but also by object-based extraction from satellite imagery (Lima et al., 2021) (Scholand and Schmalz, 2021). Actual datasets for this parameter seem lacking, but the methods mentioned need to be applied to the study area.	WaTEM/SEDEM
Bulk density, Soil organic matter content	Soil sampling and soil physical laboratory methods	Application of literature values or PTFs to soil maps	EUPTF, EUHYDI, Rosetta, LUCAS-based maps SoilGrids1km, SoilGrids250m, SoilGrids 2.0: (Hengl et al., 2014) (Hengl et al., 2017) (Poggio et al., 2021) 3D Soil Hydraulic Database of Europe (EU-SoilHydroGrids, 250m and 1km): (Tóth et al., 2017) EU-wide map (1km) based on LUCAS, BioSoil and CZO: (Aksoy et al., 2016)	EROSION-3D, CASE
Initial soil moisture content*	Parameter is highly dependent on the scenario considered; actual soil moisture before onset of an erosive event will usually need soil sampling or installed sensors (TDR, capacitive, tensiometers, ..) Ground penetrating radar: (Lu et al., 2023);	Satellite based estimation of topsoil WC (Sentinel1,2,3, radar and microwave missions); difficult to achieve temporal coverage; index of antecedent precipitation; Installed or portable cosmic-ray neutron	Can be assumed as relative degree of saturation – different scenarios (wet, dry) might need to be considered; index of antecedent precipitation: (Zhao et al., 2011) Soil water index (1km for Europe): (Bauer-Marschallinger et al., 2018), (Bauer-Marschallinger et al., 2019) EEA Daily Soil moisture of Europe (simulation, 5km)	EROSION-3D, CASE, MHYDAS, OpenLISEM

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	In any case, dedicated measuring activities are necessary and timing is important	sensors: (Heistermann et al., 2023); crop growth modelling	Regional or national predictive models (mostly drought-focused), e.g., Drought Monitor Germany: (Samaniego et al., 2013) COSMOS-Europe - cosmic-ray neutron sensor network: (Bogena et al., 2022)	
Surface roughness* (Manning's n)	Can be measured with high-resolution LiDAR or photogrammetry; temporal variation might have to be considered at this spatial scale	Assign values according to land use classification based on open channel flow literature	Based on literature values; temporal variation during cropping season difficult to consider; Extraction from SWOT data: (Emery et al., 2021) Based on SAR data: (Sadeh et al., 2018) Based on Landsat, ALOS, PRISM imagery: (Hossain et al., 2009)	EROSION-3D, IBER, CASE, SHETRAN
Aggregate stability for splash erosion	Soil physical laboratory analysis, Estimation from PTF or literature values based on detailed soil data: (Clergue et al., 2023)	Estimation from PTF or literature values, based on soil maps	Estimation from PTF or literature values, based on coarse soil data from soil maps with national or larger coverage	MHYDAS, OpenLISEM
d50, d90 soil particle diameters EROSION-3D: PSD with 9 texture classes according to German soil survey guide KA4	Soil physical laboratory analysis, sieve and sedimentation; laser diffraction; gamma-ray spectroscopy; any method suitable to obtain particle size distribution	Estimation from PTF or literature values, based on soil maps	Estimation from PTF or literature values, based on coarse soil data from soil maps with national or larger coverage	OpenLISEM, EROSION-3D
Critical shear stress (Pa) * CASE: Cohesion COH Also used as inverse function of soil cohesion	Laboratory flume experiments; field measurement with shear vane tester, penetrometer and similar devices: (Zimbone et al., 1996)	Estimation from PTF or literature values; openLISEM: (Schlesner et al., 2023)	Estimation from PTF or literature values, based on coarse soil data from soil maps with national or larger coverage	MHYDAS, CASE, OpenLISEM, EROSION-3D, WEPP
Rill erodibility (s m-1)	Laboratory flume experiments	Estimation from PTF or literature values; US case study: (Lee et al., 2022)	Default values from WEPP	MHYDAS, WEPP

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Number of rills, width, spacing, type of rills	Default values from WEPP; field inspection and survey; UAV flights: (Malinowski et al., 2023)	-	-	MHYDAS, WEPP
Density of vegetation in vegetated filter	Runoff experiments, field inspection (point frame, cover board); photographic and ALS methods: (Straatsma and Middelkoop, 2006) ; literature values	-	-	MHYDAS
Infrastructure: Buildings, Roads and Bridges or culverts Flooding barrier height	Can be captured directly (buildings, roads) or included by appropriate DEM manipulation (burning, breaching, shifting)	Sufficiently high spatial resolution of DEM or land use map needed	-	OpenLISEM
Vegetation height	Can be estimated by means of LiDAR, result of difference between DSM and DEM	Can also be estimated based on land-use information (permanent crops, forest, development stages of annual crops,..)	Vegetation height model NFI (Switzerland): (Ginzler, 2021) Global canopy height model: (Lang et al., 2023) Both datasets likely not suited for annual crops	OpenLISEM
LAI (Leaf Area Index)* SHETRAN: Vegetation cover indices CASE: Canopy cover CC	Hand-held LAI-meter; hemispherical photography; absorption of photosynthetically active radiation (PAR) above and below canopy; destructive leaf sampling (Fang et al., 2019)	Products from Copernicus Global Land Service – LAI, FCOVER (300m, 1km): (Fuster et al., 2020); Calculation from remote sensing data (NDVI-based relationships): (Bajocco et al., 2022); modelling of plant development	Calculation from remote-Sensing data; modelling of plant development; literature values specific for plant and developmental stages	OpenLISEM, SHETRAN, CASE
Drainage parameters (van Genuchten): alpha, n, specific storage, porosity	Soil sampling and soil physical laboratory methods	-	3D Soil Hydraulic Database of Europe (EU-SoilHydroGrids, 250m and 1km): (Tóth et al., 2017)	SHETRAN

			GSHP - Global Soil Hydraulic Properties dataset (250m)	
Ratio actual/potential evapotranspiration	Actual evapotranspiration measurements (Lysimeter, Eddy covariance, Scintillometer) or calculations (crop coefficients, Budyko method)	Crop growth models	NASA global ET (8km resolution): (Zhang et al., 2015) MODIS Evapotranspiration (1km resolution): (He et al., 2019) METRIC model from Landsat imagery (30 m): (Suwanlertcharoen et al., 2023) European Dataset (1 km²): (Nistor et al., 2022) Global ETa product (1 km²): (Elnashar et al., 2021)	SHETRAN
Climate information: Temperatures, solar radiation, wind velocities	Highly dependent on scenario – historical or prediction; typically complete weather station installed at site	Geostatistical interpolation from close weather station	ECMWF ERA5 (31 km): (Hersbach et al., 2023) Various historical reanalysis data from climate models: (Abbaspour et al., 2019)	WEPP
Baseline interrill erodibility (Ki) – reflects susceptibility to detachment by both rainfall and shallow flows	Calculation from Clay and very fine sand fractions – built in PTFs	-	-	WEPP
Rill erodibility (Kr)	Calculation from organic material, clay and very fine sand fractions – built in PTFs	-	-	WEPP, MHYDAS
Ground cover GC: considers soil shielded by living or dead plant matter on the soil surface	Optical	literature values, crop growth modelling		CASE,
Saturated hydraulic conductivity Ksat* SHETRAN: horizontal, vertical, relative Ksat	Spatially highly variable, feasibility of measurements at field scale and finer can be doubted (Picciafuoco et al., 2019); estimation based on PTF might be more feasible even at small spatial scales;	Prediction via PTF from soil maps EU-HYDI: (Tóth et al., 2015) (Szabó et al., 2021)	Prediction via PTF from large-scale soil maps SoilGrids1km, SoilGrids250m, SoilGrids 2.0: (Hengl et al., 2014) (Hengl et al., 2017) (Poggio et al., 2021)	CASE, MHYDAS, SHETRAN, WEPP

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WEPP: Green and Ampt effective conductivity parameter Ke	Ke: function of saturated hydraulic conductivity; Calculation from cation exchange capacity, clay and sand fractions – built in PTFs in WEPP		3D Soil Hydraulic Database of Europe (EU-SoilHydroGrids, 250m and 1km): (Tóth et al., 2017) SoilKsatDB: (Gupta et al., 2021) GSHP - Global Soil Hydraulic Properties dataset (250m): (Gupta et al., 2022) (mostly only vertical!)	
Rainfall intensity and duration Cf. considerations for RUSLE R-factor	Typically only available at sufficiently high temporal resolution (< 1hr) at existing measurement sites (ombrograph, disdrometer); in other locations: weather radar data: (Kreklow et al., 2020) Spatially highly variable. Defining design events for scenario analysis can be necessary		European scale (Matthews et al., 2022) EMO-5 (5km, 6hr) UERRA M-S (5.5km, 24hr) E-OBS (11km, 24hr) Weather radar typically has large spatial footprint	CASE, EROSION-3D

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Table 3. Advanced/experimental parameters/input data.

Parameter	Scale and datasets			Model
	Field	**Catchment**	**Regional/National**	
CF: factor for runoff concentration, considers the degree of runoff concentration sub cell-size; leads to higher shear stress and transport capacity than possible with the chosen spatial resolution	Can be calibrated with measurements for runoff and sediment masses available	Not advised, calibration likely difficult or impossible	Not advised, calibration likely difficult or impossible	CASE
Transport capacity coefficients (kTC) for different types of landuse Parcel trapping efficiency (PTEF)	Default values are available. Need to be assessed by means of calibration. Supposedly, calibration gets more complex with higher spatial resolution	Application of default values Catchment scale (CZ): (Winterová et al., 2022) (Krasa et al., 2019)	Application of default values WaTEM/SEDEM calculations at EU scale: (Borrelli et al., 2018) or at national scale (CZ): regional scale (ESP): (Alatorre et al., 2010)	WaTEM/SEDEM
Maximal transport coefficient from interrill erosion	Calibration needed; application of default values	Application of default values	Application of default values	MHYDAS
Boundary conditions, including rainfall intensity, in- and outlet hydrograph and sedigraph SHETRAN: stream-aquifer interaction	Appropriate measurements	Boundary conditions can be either set at specific locations, or spatially interpolated, e.g., from a network of rain gauges.	While interpolation of rainfall intensities between stations on regional/national scale seems unproblematic, boundary conditions for hydro- and sedigraphs can be difficult to obtain. Sedigraphs are often not available with sufficiently high spatial and temporal coverage. Hydrographs are typically only known at river gauges. This presumably limits model application to catchment areas with measurement infrastructure in place.	IBER, SHETRAN

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3 Conclusions

The erosion models investigated share many commonalities in their parametrization. Especially the RUSLE factors R, K, LS, C, P are engrained into the structure of most of the models. Because their use is so widespread, finding appropriate datasets for these parameters at different spatial scales is comparatively easy.

Some model-specific parameters are shared between the models investigated, these include saturated hydraulic conductivity, initial soil water content, and soil stability with regard to rainfall or runoff detachment. Improving or creating the respective datasets seems beneficial to the wider erosion modelling community and not only the users of one specific model.

Naturally, more process-based models tend to have higher demand for parameters that are more difficult to obtain. These are either model-specific but generally attainable by simple means (PTFs, literature values), or they have to be obtained by parameter calibration, using measurements for the model outputs. This mostly means two things: while the simpler models can be used without the need for calibration data, the more advanced ones need both measured data and specialist knowledge for application.
According to the quality of the dataset in question, using default relationships such as literature values or PTFs might be more or less feasible than using the respective dataset (this behaviour is presumably highly model-specific and would need proper investigation by dedicated studies). The WEPP model seems to be well-equipped to work in data-scarce regions, with PTFs included for most parameters (although mostly based on US soils). As can be expected, the more physical/hydraulics-based models Erosion-3D, SHETRAN and IBER tend to need more advanced parameters that are hard to obtain at larger spatial scales.

With parameter values depending on soil properties when using literature values or PTFs, the reliability of these values depends on the reliability of the soil dataset in use. There are typically national soil maps available in many countries (existing for taxation or pedological purposes). Apart from that, various regional, national or even global-scale datasets exist that can be used when lacking any more detailed information. High-resolution data is becoming increasingly available for a range of scales, thereby extending the possible modelling scales, however it is uncertain whether the models are equipped for such an up- and down-scaling (Epple et al., 2022). With recent advances in digital soil mapping applications, utilizing remote sensing data and machine learning models, the erosion modelling community can hope for improved availability and accuracy of these data. Dataset quality and its inherent uncertainties should be kept in mind throughout the modelling and when reporting its results.

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