Towards climate-smart sustainable management of agricultural soils

SCALE

Managing Sediment Connectivity in Agricultural Landscapes for reducing water Erosion impacts

Deliverable WP4-D5

Stepwise tutorial for USLE approach with different dataset qualities and scales

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Abstract

Erosion risk assessment via models is a critical tool for soil erosion mitigation planning, applicable both at local scales for specific control measures and at larger scales for identifying erosion hotspots. This study examines the effects of up- and down-scaling on soil erosion risk models by analysing datasets of varying scales and input data accuracy, focusing on the Universal Soil Loss Equation (USLE) and its derivatives. Specifically, we assess the rainfall erosivity factor (R-factor) and the soil erodibility factor (K-factor) within the Hydrological Open Air Laboratory (HOAL) Petzenkirchen catchment in Austria, utilising datasets ranging from European to national and local scales. The methodology involves using long-term precipitation and temperature data, along with soil characteristics from the HOAL catchment. The USLE model, which calculates mean annual soil erosion, incorporates various environmental and management factors. For R-factor computation, both national and local datasets were analysed using multiple kinetic energy-intensity (KE-I) equations and direct measurements from a disdrometer were employed for validation purposes. Results indicate that R-factor estimates from national and local datasets are generally comparable, with differences arising from the use of different KE-I equations and spatial interpolation methods. The national dataset, derived from 171 rainfall stations and SPARTACUS grid data, provided an R-factor of 78.72 N h^{-1} yr^{-1}. Local dataset calculations showed minor differences, with the van Dijk et al. (2002) equation yielding an R-factor of 76.37 N h^{-1} yr^{-1}. Direct disdrometer measurements produced an R-factor of 76.68 N h^{-1} yr^{-1}, aligning well with both national and local estimates but highlighting the need for a longer dataset for reliable results. For the K-factor, substantial variability was observed across different methods and scales. The LUCAS dataset was used for large-scale analysis, while a detailed soil sample network within the HOAL catchment provided local data. The Williams et al. (1983) method resulted in the highest K-factor for the large-scale dataset (0.07), whereas the Wischmeier and Smith (1978) method yielded the highest average value (0.082) for the local dataset. The study underscores the importance of accurate in-situ soil data and the limitations of interpolation methods, emphasizing that precise soil texture information is crucial for reliable K-factor estimation. Large-scale datasets are useful for identifying general erosion risk hotspots. However, for effective erosion mitigation planning and detailed measure design, validation with local high-accuracy data is essential. The study advocates for a standardised approach to up- and down-scaling in soil erosion modelling to ensure consistency and comparability of model outcomes. Advanced interpolation techniques and the integration of multiple data sources, including remote sensing and radar data, can enhance the precision of soil erosion risk assessments, thereby supporting more effective soil conservation strategies.

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1 Introduction

Erosion risk assessment via models is a valuable tool for soil erosion mitigation planning at both local and larger scales. Locally, these models can guide the implementation of specific control measures, while at larger scales, they can identify erosion hotspots. However, as highlighted in our survey of soil erosion model use in Europe (Schmaltz et al., 2024), there is significant variability in parameterisation and methodology across different modelling approaches, even when the same model is employed. This variability hampers the comparability of model outcomes and can potentially distort erosion mitigation planning and implementation.

The accuracy and quality of model input data are critical for the validity of model outcomes. Dataset quality is often linked to the modelling scale, with large-scale modelling efforts requiring substantial data that may not always be available in appropriate quality or accuracy across the entire modelled area, such as at a national level.

The aim of this report is to enhance our understanding of the up- and down-scaling effects on soil erosion risk models. We conduct modelling scenarios using datasets of varying scales and input data accuracy, ranging from data available at the European scale to data available at national and catchment scales. To illustrate the impact of changing datasets and methods, we analyse two specific modelling parameters within the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and its derivatives (Renard et al., 1997; USDA-ARS, 2013): the rainfall erosivity factor (R-factor) and the soil erodibility factor (K-factor), within a specific catchment in Austria. These factors were chosen due to their physical nature and the potential for validation. Both factors require spatially distributed data at larger scales, which can introduce uncertainty in their estimation due to the limited availability of highly accurate data at large spatial scales.

2 Methodology

The Hydrological Open Air Laboratory (HOAL) Petzenkirchen, in Lower Austria was chosen as the study site (Blöschl et al., 2016) to ensure the availability of datasets at various scales. The catchment size is 65.8 ha and the long-term (1990–2014) mean annual precipitation and temperature at the site are 823 mm and 9.5°C. The elevation ranges from 268 to 323 m a.s.l. with a mean slope of 8%. The soil type of the area is mainly cambisol and the majority of the catchment area is used for arable land.

The USLE model (and its derivatives) is the most widely used model for soil erosion risk assessment and includes several factors to estimate soil erosion. It estimates the mean annual soil erosion, A (in t ha^{-1} yr^{-1}) over a predefined period considering different environmental and agricultural management factors:

$$A = R * K * L * S * C * P \qquad \textbf{Eq. 1}$$

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where R is the erosivity factor and K is the erodibility factor. L and S are slope length and steepness factors, respectively, which depict a combined topographic LS-factor. C is the cover management factor and P is a protection factor in case soil protection measures are set.

Computation of rainfall erosivity

Rainfall erosivity (R-factor) is a significant parameter influencing soil erosion, as the detachment and mobilisation of soil particles is initiated by raindrops. Rainfall erosivity depends on the rainfall kinetic energy and rainfall intensity and can be highly variable in time and space depending on the rainfall characteristics of a specific area.
R-factor calculation was done according to the same method as described in Johannsen et al. (2022), who updated the R-factor estimation of Austria. Here the event erosivity, EI_{30} (N h^{-1}), was calculated as by the standard definition of the USLE (Wischmeier and Smith, 1978):

$$EI_{30} = \left(\sum_{r=1}^{k} e_r \, v_r \right) \mathrm{I}_{30} \qquad \textbf{Eq. 2}$$

where e_r is the kinetic energy (kJ m^{-2} mm^{-1}), v_r is the rainfall volume (mm) in period r and I_{30} is the maximum rainfall intensity (mm h^{-1}) within 30 minutes of the event.

The R-factor (N h^{-1} yr^{-1}) is the average of annual erosive events over a certain number of years:

$$\mathrm{R} = \frac{1}{n} \sum_{\mathrm{j}=1}^{\mathrm{n}} \sum_{\mathrm{k}=1}^{\mathrm{m_j}} (EI_{30})_k \qquad \textbf{Eq. 3}$$

where n is the number of years in the time series, m_j is the number of erosive events within a year j and EI_{30} is the rainfall erosivity of event k.

Kinetic energy of rainfall can be calculated when the raindrop size and velocity is known. This information is often not known and thus kinetic energy-intensity (KE-I) equations have been developed. These are empirical relationships that have been established through site-specific rainfall measurements and enables the estimation of kinetic energy by knowing the rainfall intensity only. A large variation in KE-I equations (linear, exponential, logarithmic and power law) exists due to the use of different measurement methods, sampling limitations and variations in geographical and meteorological conditions. The KE-I equations are thus often only valid under the conditions on which they were calibrated (Johannsen et al., 2020b). In the study by Johannsen et al. (2022), the KE-I equation by van Dijk et al. (2002) was used, as this equation was developed as a universally predictive equation based on data from scientific literature. It has also been shown to fit the best with measured kinetic energy in the HOAL catchment (Johannsen et al., 2020b). Other commonly used KE-I equations are the ones used in the USLE, RUSLE and RUSLE2 by Wischmeier and Smith (1978), Brown & Foster (1987) and McGregor et al. (1995), respectively.

For analysis of the effect of using different KE-I equations, the local dataset was calculated with several KE-I equations (Table 1).

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Table 1. KE-I equations of different studies.

Equation number	KE-I equation	Reference
1	$KE = 28.3(1 - 0.52e^{-0.042I})$	van Dijk et al. (2002)
2	$KE = 29(1 - 0.72e^{-0.05I})$	Brown & Foster (1987)
3	$KE = 29(1 - 0.72e^{-0.082I})$	McGregor et al. (1995)
4	$KE = 11.9 + 8.73 \log I$, for $I \leq 76$ mm h^{-1} $KE = 28.3$, for $I > 76$ mm h^{-1}	Wischmeier & Smith (1978)

Large-scale dataset

The national dataset is taken from the paper by Johannsen et al. (2022), who updated the Austrian R-factor estimation using 171 rainfall stations and mapped the whole country by linear regression and use of the SPARTACUS daily precipitation and temperature 1 km^2 grid cell datasets (Hiebl and Frei, 2018, 2016). The R-factor from the national dataset was based on R-factors calculated from individual rain gauge stations across Austria (between 1995-2015), which were then used to make a linear regression of R-factors and mean annual rainfall for the whole of Austria. This regression was then applied to the gridded SPARTACUS annual rainfall dataset, thereby creating an R-factor for each 1 km^2 grid cell, to spatially estimate R-factors also in those areas without a rainfall measurement station. For this study, the R-factor of each of the three SPARTACUS cells covering the HOAL catchment (Figure 1) were averaged together to give the combined R-factor for the catchment.

For further information we refer to the paper by Johannsen et al. (2022).

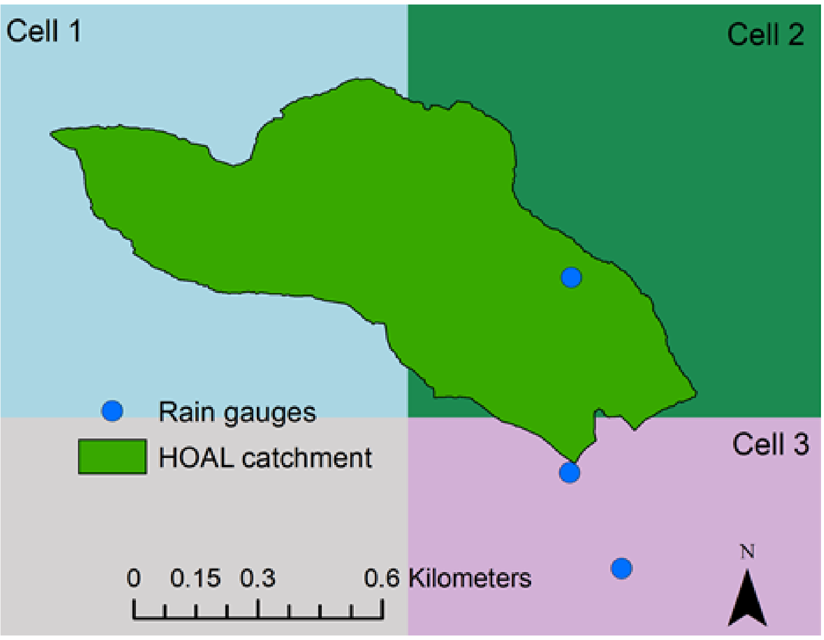

Figure 1. The three 1 km^2 SPARTACUS cells (Cell 1 to 3) of mapped R-factors by Johannsen et al. (2022) covering the HOAL catchment (green outline) and the three rain gauges (blue dots) used to compile the full local dataset.

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Local dataset

The local dataset consists of 5-min data from three rain gauges situated within or near the HOAL catchment (Figure 1). The dataset covers 1995-2015, but had to be combined from three rain gauges in order to cover the whole period. The events on days with negative temperatures were excluded based on the SPARTACUS temperature dataset (Hiebl and Frei, 2016), but only "Cell 2" in HOAL (Figure 1) was used for the temperature correction, as the three cells rarely differed in their frost days.

The same calculation method of event erosivity and R-factor calculation (as described above) was performed for the local dataset as for the national dataset (without the data correction process though). As this local dataset only describes a single site, no spatial interpolation to the SPARTACUS cells was done. The local dataset R-factor estimation method thus differs from the national dataset on the point of interpolation to a larger scale.

To test the effect of using different KE-I equations the local dataset was run with several different equations (Table 1).

The use of disdrometer data allows for direct estimation of the EI30 (R-factor) directly based on the measured drop size and velocity and intensity, without relying on a KE-I equation for calculating kinetic energy and as such should give a directly measured R-factor. A disdrometer (PWS100, Campbell Inc.) is situated in the HOAL catchment and provides data in 1-min resolution. Unfortunately, the dataset is rather limited and only starts at the very end of the 1995-2015 time period covered by the other datasets. Available disdrometer data for the years 2014, 2015 (incomplete year) and 2017 were used for the calculation. Kinetic energy was calculated based on the drop size and velocity measured by the disdrometer. The intensity was measured directly by the disdrometer. Rainfall events were separated and KE and I were summed up for every event. The R-factor was calculated as per Eq. 2 and 3.

Computation of soil erodibility

The soil erodibility (K-factor) reflects the natural ability of topsoil to erode. Soil erodibility depends on the specific soil characteristics such as soil texture, organic matter content, rock fragments, etc. and thus varies a lot depending on these factors, which are highly spatially variant. A spatially explicit estimation of the K-factor is therefore critical in soil erosion modelling and soil loss mapping.

However, the need for accurate, spatially distributed soil data makes the K-factor estimation difficult at larger scales, due to data availability limitations, differing spatial resolutions or degree of needed data content for the specific parameters within the K-factor calculation. Furthermore, several calculation methods exist, which use different input data and empirical relationships for calculation. This may lead to a high uncertainty in the K-factor estimation at regional/national level, thereby also affecting possible soil erosion estimates.

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Table 2. K-factor equations of different studies.

Eq. number	K-factor equation	Reference
5	$$K = \frac{((2.1M^{1.14}(10^{-4})(12-OM) + \big(3.25(b-2)\big) + (2.5(c-3))}{100}$$ where M is the particle size parameter, OM is soil organic matter, b is the soil structure code used in soil classification and c is the profile permeability class.	Wischmeier and Smith (1978)
6	$$K = \frac{7.594\left(0.0034 + \frac{0.0405\exp\left(-\frac{1}{2}\left(log_{10} DG + 1.659\right)\right)}{0.7101^2}\right)}{10}$$ where DG is diameter of the grain, i.e. soil particle.	Römkens et al. (1997)
7	$$K1 = \begin{cases} 2.77 * 10^{-5} f_{sivfs}(100-C)^{1.14}, if\ f_{sivfs} < 70\ \% \\ 1.75 * 10^{-5} f_{sivfs}(100-C)^{1.14} + 0.0024 f_{sivfs} + 0.16 \end{cases}$$ where f_{sivfs} is the fraction of silt and very fine sand. $$K2 = \begin{cases} \frac{10-OM}{10}, if\ OM > 4\ \% \\ 0.8, else \end{cases}$$ where OM is the organic matter content. $$K3 = \begin{cases} K1K2 + 0.043(s-2) + 0.033(p-3), if\ K1K2 > 0.2 \\ 0.34K1K2 + 1.79(K1K2)^2 + 0.24K1K2s + 0.033(p-3) \end{cases}$$ where s and p denote stoniness and soil permeability class indicators. $$K4 = \begin{cases} \frac{K3}{10}, if\ f_{stone} < 1.5 \\ \frac{K3(1.1\exp(0.024 f_{stone}) - 0.06)}{10} \end{cases}$$ where f_{stone} is the fraction of surface stones.	Nomograph (according to Auerswald et al., 2021)

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8	$$K = (0.2 + 0.3\exp\left(0.0256S\left(1 - \frac{Si}{100}\right)\right)\left(\frac{Si}{C+Si}\right)^{0.3}\left(1 - \frac{0.25C}{(C + \exp(3.72 - 2.95C))}\right)\left(1.0 - \frac{0.7S}{(sn + \exp(-5.51 + 22.9S))}\right)/10$$ where S, Si and C are sand, silt and clay fractions (%), respectively.	Williams et al. (1983)
9	$$K = \frac{0.0086Si}{10}$$ where Si is the silt content (%).	Strauss et al. (2007)
10	$$K = ((\frac{2.1\left(S(100 - C)\right)^{1.14}10^{-4}(12 - OM)\big)}{100}0.1317$$ Where S and C are sand and clay contents, respectively and OM is the organic matter content (all in %).	Wischmeier et al. (1971)
11	$$K = \left((0.043pH) + \left(\frac{0.62}{OM}\right) + (0.0082S) - (0.0062C)\right)Si$$ where pH is the pH of the topsoil, OM is the organic matter content, S, Si and C are percentages of sand, silt and clay fractions respectively.	David (1988)

Large-scale dataset

The large-scale dataset employed in this study is the LUCAS dataset, which is also utilised in the computation of the K-factor as described by Panagos et al. (2014). For the purposes of this study, only LUCAS data points located within Austria and on arable land were selected. The LUCAS dataset includes three texture classes (sand, silt, clay), organic matter content and information about the topsoil's pH. Furthermore, stone content and surficial stone coverage data were extracted from the EU's soil database, as documented by King et al. (1994). The K-factor was computed using the equations referenced in the aforementioned study. If necessary, the very fine sand fraction was estimated to be 20% of the sand fraction, following the methodology of Panagos et al. (2014). The resulting datasets were spatially interpolated using Kriging with the R programming language. The interpolation was performed on a raster with a resolution of 25 x 25 metres. Subsequently, the interpolated K-factor values specific to the HOAL catchment area were clipped out for further analysis.

Local dataset

The local dataset is comprised by a soil sample network with a raster resolution of 50 x 50 metres, which encompasses approximately 60 hectares of the catchment area. The dataset

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comprises topsoil samples categorised into seven texture classes: fine, medium and coarse sand; fine, medium and coarse silt; and clay. Furthermore, the dataset encompasses data on organic matter content, topsoil pH and the quantity of coarse material (particles exceeding 2 mm). Furthermore, data on the surface coverage of coarse material are available and are representative of the predominant soil types within the study area.

3 Results and Discussion

R-factor

The national R-factor estimation by Johannsen et al. (2022) was used to calculate the averaged R-factor of the three cells with mapped annual R-factors covering the HOAL catchment (see Fig. 1) and gave an R-factor of 78.72 N h^{-1} (Table 3).

Table 3. R-factors from the three different datasets and calculated with different KE-I equations for the local dataset.

	R-factor (N h^{-1} yr^{-1})	
KE-I eq.	**National dataset**	**Local dataset**
van Dijk et al. (2002)	78.72	76.37
Brown & Foster (1987)	-	66.98
McGregor et al. (1995)	-	74.67
Wischmeier & Smith (1978)	-	78.02

The difference in R-factor between the national dataset and the local dataset is only 2.35 N h^{-1} yr^{-1}, when using the same R-factor calculation method and KE-I equation. As the data correction process and the spatial interpolation step were not done for the local R-factor calculation, the calculation methods cannot be said to be exactly comparable. However, the local scale dataset can rather be seen as an effort to validate the R-factor estimation based on the national dataset.

Both the local and the national dataset are based on rain gauge measurements. These are single point data sources, which are often unevenly distributed in space and themselves subject to measurement inaccuracies. To extend the R-factor estimations over a larger region, interpolation methods are used. Several such spatial interpolation methods exist, each with their own advantages and drawbacks, which have to be kept in mind.

Other possible large-scale datasets could be the use of radar rainfall data. Such datasets have already been used e.g. in Germany to produce a new R-factor estimation for the whole country (Auerswald et al., 2019). As radar provides a contiguous data source, there is no need for interpolation, which eliminates one source of uncertainty. Recently, also remote sensing developments have led to satellite data being used to estimate the R-factor over large scales e.g. in India (Das et al., 2022).

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Like any other measurements radar and satellite data have their own uncertainties and performance limitations. Therefore, recent products tend to combine multiple data sources to obtain high-precision rainfall data (e.g. the INCA dataset in Austria), e.g. by correcting the errors or data gaps from radar or satellite data with rain gauge data. Given the inherent uncertainties of each measurement method and differences in spatial and temporal resolution, the combination of multiple rainfall datasets is a challenging task (Wang et al., 2024).

From Table 3, it can be seen that some differences in the final R-factor occurs as a result of using different KE-I equations, although the differences are not that great for three of the KE-I equations. However, the Brown & Foster (1987) equation underestimates the R-factor compared to the others. This is a well-known phenomenon and its use has been discouraged (Johannsen et al., 2020b; Nearing et al., 2017), however it is still very much being used.

The use of disdrometer data could be used for R-factor validation purposes and to eliminate the use of KE-I equations. Disdrometers can directly measure the drop size and velocity of rainfall drops, whereby the kinetic energy can be directly calculated and the use of empirical KE-I equations can be avoided. The direct measurement of erosive events by a disdrometer within the HOAL catchment resulted in the calculation of an R-factor of 76.68 N h^{-1} yr^{-1}. This R-factor actually fits well with the national and local scale R-factors. Due to the limited dataset the result is however very uncertain. A longer time period of recorded disdrometer data is needed to produce a reliable R-factor. Although the use of empirical KE-I equations can be avoided by direct kinetic energy measurement with a disdrometer, as with any measurement device, disdrometers also have their own measurement uncertainties (Johannsen et al., 2020a) and the results have to be analysed and interpreted with this in mind.

K-factor

The K-factor methods produce significant differences for both dataset scales, with variations of approximately +/- 0.035 of the K-factor. Notably, Williams et al. (1983) reported the highest K-factor of 0.07 for the large-scale dataset. In contrast, the method by Wischmeier and Smith (1978) exhibited the highest average value of 0.082 for the local dataset. On the other hand, the method proposed by David (1988) resulted in the lowest value for the large-scale dataset at 0.026, while the Roemkens et al. (1997) method recorded the lowest average K-factor for the local dataset (Figure 2).

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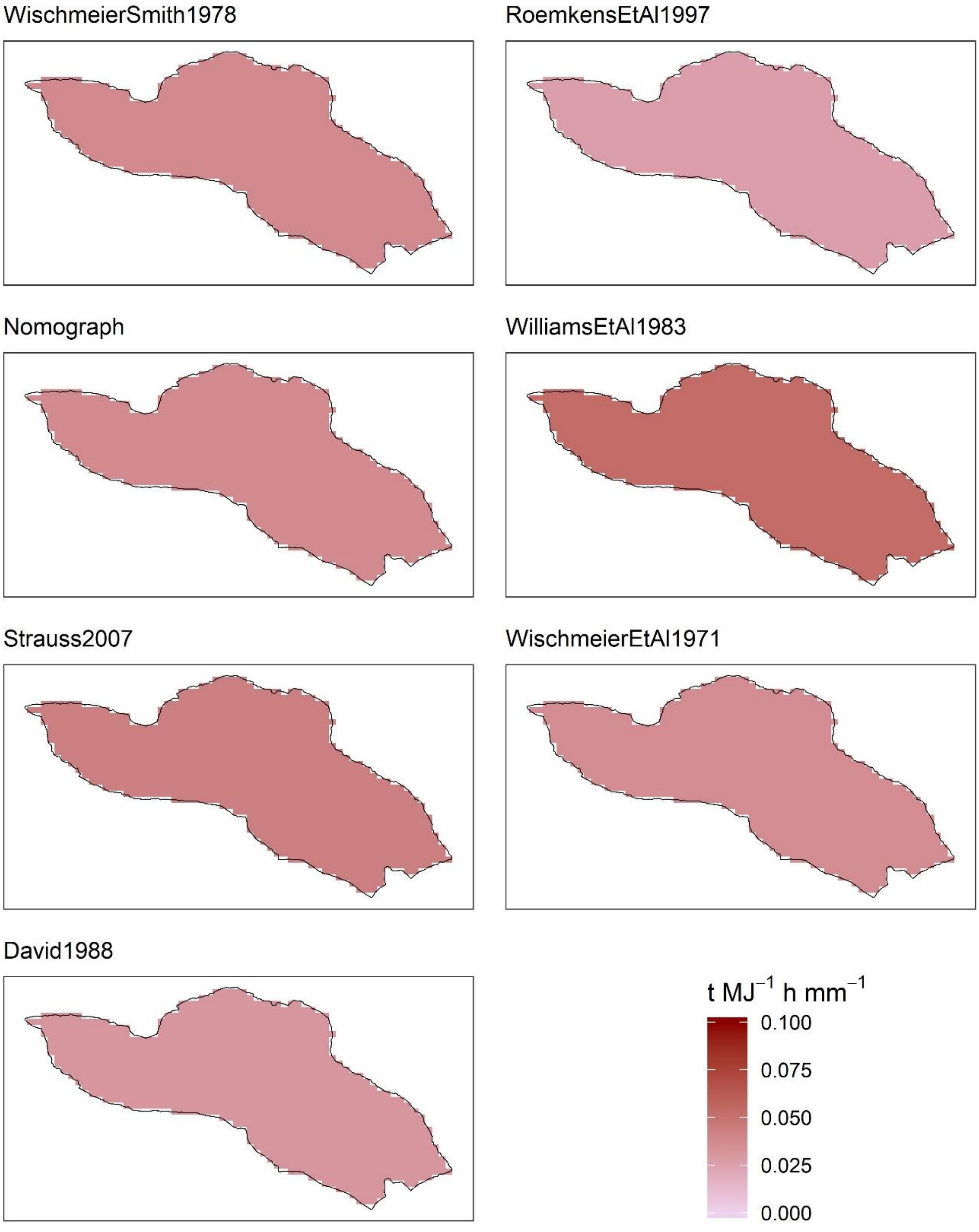

Figure 2. K-factors with applied methods and the large-scale dataset for the HOAL catchment.

At the local scale (Figure 3), various methods demonstrated similar tendencies in K-factor distribution, with higher values observed in thalweg situations and lower values at hilltops. However, there is considerable variability among the methods, with certain spatial outliers, such as the David (1988) method, exhibiting high variability. When comparing the two datasets, methods showed increased variability, particularly when the computation heavily relied on very fine sand, as seen in the methods by Wischmeier and Smith (1978) and Wischmeier et al. (1971).

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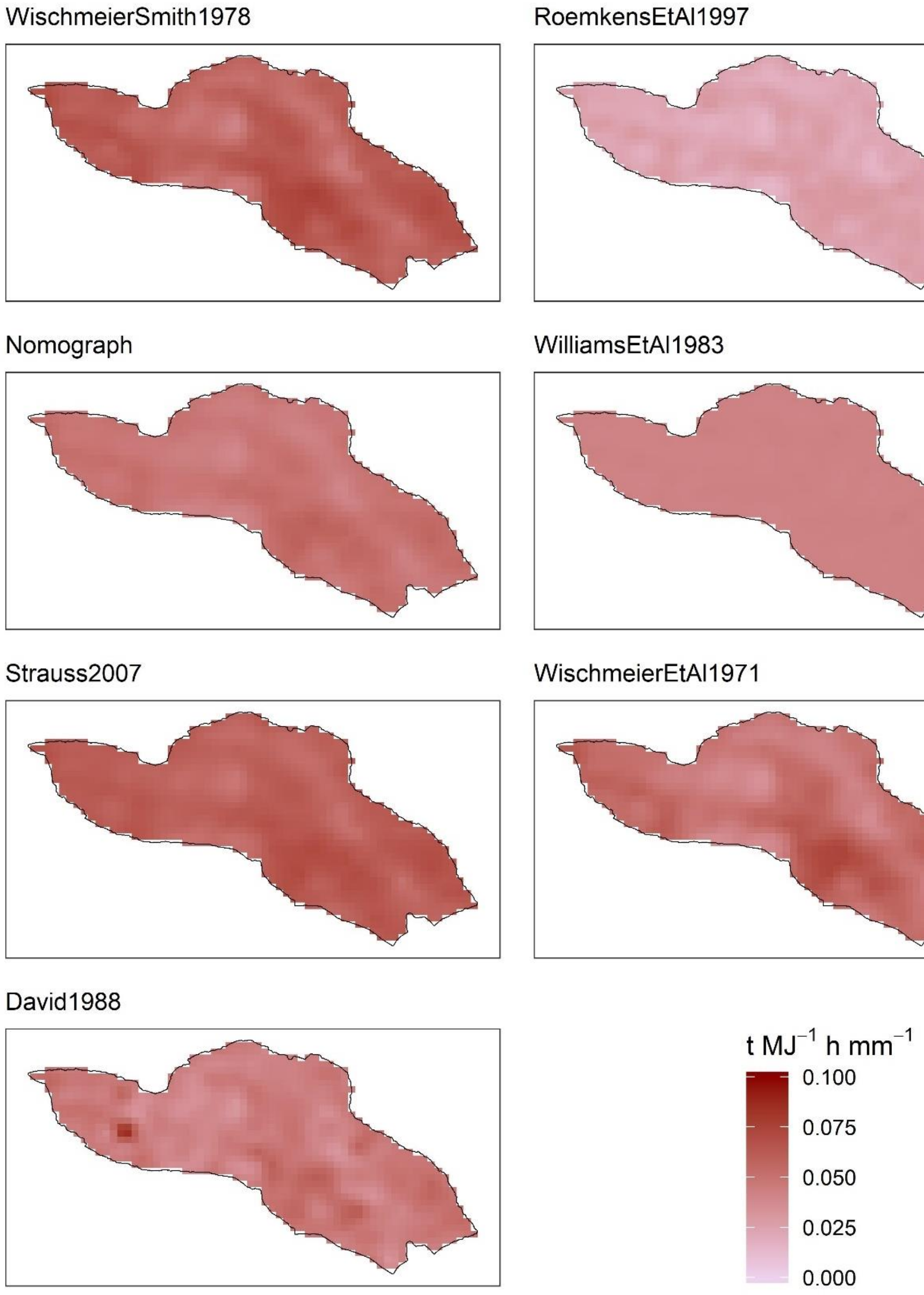

Figure 3. K-factors with applied methods and the local dataset for the HOAL catchment.

The importance of in-situ information about soil textural composition becomes evident, as accurate soil data are crucial for reliable K-factor estimation. The method by Strauss et al. (2007), which exclusively includes silt content, also emphasises the need for precise in-situ information. Meanwhile, methods by Roemkens et al. (1997) and the Nomograph methods appear to be less sensitive to the scale dependencies of the dataset.

While interpolation methods can be a temporary solution in the absence of data, measured data remains critical for accuracy. Advanced interpolation techniques, including statistical methods or those employing artificial intelligence, could potentially enhance interpolation results in regions with data scarcity. Ensuring data accuracy is fundamental to achieving more precise K-factor estimates on a catchment scale, thus emphasizing the necessity to consider very fine sand fractions in relevant methods.

4 Conclusions

The study highlights the challenges and implications of scaling effects on soil erosion risk models, emphasizing the importance of parameterisation and dataset accuracy in the Universal Soil Loss Equation (USLE) application. By comparing the rainfall erosivity factor (R-factor) and soil erodibility factor (K-factor) using both national and local datasets within the HOAL catchment in Austria, this research underscores the complexities involved in soil erosion modelling at different scales.

The methodology employed utilised the Hydrological Open Air Laboratory (HOAL) Petzenkirchen as the study site to leverage datasets available at various scales. For the R-factor, data from national datasets were interpolated from rain gauge stations across Austria, while local datasets were derived from three rain gauges within the HOAL catchment. The study also incorporated direct measurements from a disdrometer to validate R-factor calculations. The results revealed that despite methodological differences, R-factor estimates from national and local datasets were comparable, although certain empirical equations, like the one proposed by Brown & Foster (1987), were found to underestimate the R-factor significantly.

Similarly, for the K-factor, the study employed the LUCAS dataset for large-scale analysis and a detailed local soil sample network within the HOAL catchment. The results indicated substantial variability in K-factor estimates across different methods and scales, with the Williams et al. (1983) method yielding the highest K-factor for the large-scale dataset and the Wischmeier and Smith (1978) method for the local dataset. The spatial variability of K-factor estimates highlighted the importance of accurate in-situ soil data and the limitations of interpolation methods in the absence of detailed soil texture information.

We conclude that large-scale datasets can effectively identify general erosion risk hotspots, but for precise planning and implementation of erosion mitigation measures, validation with local, high-accuracy data is essential. The need for a standardised approach to up- and down-scaling in soil erosion modelling is evident to ensure consistency and comparability of model outcomes. Advanced interpolation techniques and the integration of multiple data sources, including remote sensing and radar data, may enhance the precision of soil erosion risk assessments, thus supporting more effective soil conservation strategies.

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