We are grateful for the careful, proficient and helpful review of our manuscript. Our replies are inserted in blue in the following.

Interactive comment on

"Rain erosivity map for Germany derived from contiguous radar rain data"

By Franziska K. Fischer et al.

A. Vrieling (Referee)

a.vrieling@utwente.nl

Received and published: 24 October 2018

I really like the fact that the authors have used rainfall radar data to map rainfall erosivity at the national scale. This is a great follow up from earlier papers that advocated the use of gridded rainfall estimates for this purpose, with the present ground-based radar data having a clear advantage over satellite-derived data in terms of their accuracy and spatial and temporal resolutions. As such, I much support its publication. Nonetheless, I do have a number of concerns regarding the methodology and also the write-up of the work, which at times is unclear and poorly structured. The main concerns are:

1. My main issue with the manuscript is its poor readability. Many statements are un- clear, often lacking precision; for example a reader sometimes needs to guess what data the authors refer to precisely. Further, I also note a mixing of results in the methods section, and a repetition of methods in the discussion section. I realize that my statement regarding the poor readability is rather general, but I try to specify as good as I can specific instances in the detailed comments section below. However, in general the feeling I obtained was that the authors should do one step back from their research and make their text more accessible by taking more a perspective of readers that are less familiar with what the authors did. Finally, also the alignment between section headings in methods and results could be better for easier understanding of what results belong to which methods.

We carefully edited the manuscript in order to improve its readability and to remove any ambiguity.

2. The main analyses that result in the erosivity map were performed using 1-hr radar data. This is partially justified by the authors due to the amount of data to be processed (P5L9-12). While data reduction can be an advantage for calculations, I still wonder though whether this is the best effort possible. Rainfall erosivity is by definition dictated by intensity and intensity is much better captured with 5-minute data. The reported advantage of the adjustment to rain gauge measurements could also hold for 5-minute data, i.e. it should be easy to re-assign the 1-hr adjusted data to the 5-minute intervals. This leaves me wondering if we would not get to better estimates if we take advantage of the 5-minute intervals. I agree that data storage and processing requirements will increase, but with a smart computer code it should not be too hard to calculate through 17 years of 5-minute data. While I do not necessarily request the

authors to change this now (although I would applaud it), I would at least expect a discussion as to whether future improvements of their map is possible, given also that they admit that "high intensity peaks" (P13L4) are very important for erosivity.

We fully agree that we would get better results for maps of PAST erosivity (= "hindcast" erosion modelling) if we would use 5-min data and we have shown this in Fischer et al. (2018). Usually such maps are useful for shorter time scales (event, year) for comparison with recorded erosion damages. Long-term average maps are usually applied for PLANNING (= "forecast" erosion modelling). In this case we do not need the exact location of a thunderstorm cell in the past but the general pattern that can be expected. This requires smoothing of the stochastic locations.

We added an extensive overview over the two types of R factor use and the smoothing that is inherent in present R maps.

3. I do not fully understand why the authors chose to present erosivity at the daily time scale, and this raises two questions.

This is a misunderstanding. We did not consider days (see below, your Point 3.B). Days were only considered for the seasonal EI distribution where it is necessary. In this case an event, even if it extended over several days, was assigned to that calendar date that was in the middle between the start and the end of the event.

A) Yes, we know that erosivity is stochastic so the scatter in Figure 5 is hardly a surprise. However, the main question eventually is how erosivity is combined with other factors (e.g. vegetation) to estimate erosivity. Arguably this could be at the daily time scale, but also weekly or monthly could provide sufficient temporal detail and as an additional advantage would have a smoothing effect in itself.

Yes, this is the basis for the crop stage period of the C factor. However, the crop stage periods between crops appear at different dates and current developments (RUSLE) allow for a continuous calculation of the soil loss ratio. A classification of the seasonal distribution (e.g. monthly means) will always decrease the accuracy of C factor calculations (except for the unlikely case that crop stages change only at the beginning of months) compared to daily values (note that these daily values are not daily events but the fraction of annual erosivity that on average can be expected to occur at a certain day).

B) Because the paper partially focuses on daily erosivity, I was curious to know how the authors dealt with night-time rain events. A storm can occur overnight thus belonging to two days. Nonetheless, as a single event, this should be treated accordingly as such when aggregating for a year. Any insight in this would help.

We did not distinguish between day-time and night-time but strictly followed the recommendations by Wischmeier. Often the events extended over midnight (because they often start in late afternoon and end in the early morning hours) or they extended even over several days. Our calculations did not use days but continuous temporal records over 17 years. We clarified this in the text.

4. Although I understand part of the reasons for smoothing, particularly for presenting average annual erosivity, I found little justification for the methods used in this study. Rather mechanistically it is described what is done, but reasons are mostly lacking. An example of this is P7L9-15: a sequence of three temporal filters are applied. I wonder whether a single carefully chosen filter would not suffice. The poor justification is also true for the procedure described in P5L20-22 on scaling: how were those parameters determined?

We added to the Introduction a better description of the twofold and contrasting applications of R maps and a description of the strong smoothing that has been unintentionally applied in previous maps. Furthermore, we replaced 'filtering' by 'smoothing' because filtering is often understood as removing certain (regular) frequencies while the occurrence of erosion events is stochastic.

To answer the question more specifically: An individual smoothing algorithm did not work (and cannot work). Even if one would exist, there would be no advantage for the reader or user of the data. The length of description of the method overemphasizes the importance of smoothing. The cumulative distribution function of the raw data correlates with the cumulative distribution function of the smoothed data with $r^2=0.9998$ ($n=365$). This information was added to the manuscript

5. I wonder why the authors' main interest seems to obtain a smooth average annual erosivity map. This leaves me wondering what they see as the main application of this map; the general statement in P1L25 (and P13L20) makes some sense but could be further elaborated. I would argue that if the interest is mostly (or partially also) in erosion monitoring, we may not need any smoothing at all, but rather we want to know when, where, and to what extent a surface is exposed to erosive rainfall. In this case we would not want to smooth out the stochastic nature of the erosivity, but rather retain it, because it offers important insights on erosion occurrence and could directly be combined with temporal vegetation assessments (e.g. from satellites). While I do not mean to necessarily promote own work, the discussions in https://doi.org/10.1016/j.gloplacha.2014.01.009 could be of interest in this regard (in which actually I also stated the potential interest of ground-based weather radars for the purpose of erosivity assessment!).

We added to the Introduction a better description of the twofold and contrasting applications of R maps and a description of the strong smoothing that has been unintentionally applied in previous maps.

6. Despite some of the comments above, Figure 5 is an important result in my view. I understand that this is an average within-year distribution for Germany, but I miss a discussion (and/or results) that show the seasonal distribution for sub-regions. Perhaps it would also be an idea to show monthly maps?

We added a sentence and a figure in the appendix to show the (non-existent) regional variation.

“There was no detectable difference in the seasonal variation between different regions in Germany (see Fig. A5 in the Appendix). The cumulative density functions of different regions correlated with at least $r^2 = 0.998$ ($n = 365$).”

7. The authors frequently refer to the R map of Sauerborn (1994). It would be helpful if this map could be provided (e.g. in the Appendix) using the same color scheme as used for the other maps.

We added it as Fig. A2

8. A trend in erosivity is proving through comparison with the older map, and (luckily) also comparing within existing rainfall stations. Because the authors also have a 17-yr series of erosivity, I wondered if that could also be a basis to say something about a (spatially-aggregated) time series for that period. Particularly as the authors report a large trend in the last few decades (P12L5).

We added to the discussion

A time series of 17 yr is regarded too short in meteorology for calculating temporal trends. The data in Sauerborn (1994) were derived from different periods for different states. If we calculate the state-wide mean R factors from her transfer functions relative to the state-wide mean R factors of the radar-derived map and plot this relative R factor against the mean year from which the state-specific data originated, a 23-yr long period can be covered by the means (Fig. 7; years < 1990; the total time period of individual years covers an even wider range, mostly about ± 5 yr around the mean year). During this period there was a slight but insignificant increase in erosivity with time. This increase smoothly leads over to the steeper increase in relative R for the radar-derived Germany-wide annual R factors if we express them again relative to the 17-yr mean (Fig. 7; years > 2000). Combining both data sets covers more than 60 years and yields a very highly significant regression ($r^2 = 0.6388$, $n = 28$). This regression indicates that at the end of the radar time series (2017) the R factor likely is already 20% higher than the values depicted in Fig. 2. There was no offset between both time series, which could indicate that high values obtained from the radar data are caused by the differing method. Rather, this time series again corroborates that the large increase in R is not a methodological artefact but due to accelerating climate change.

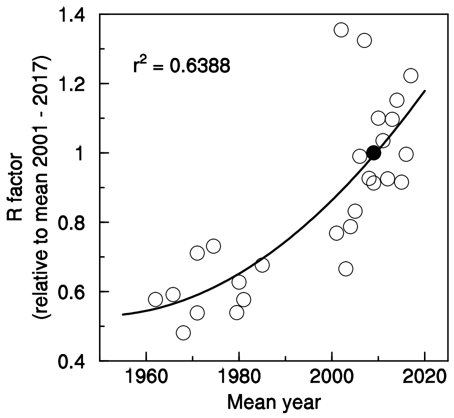


Fig. 7: Average R factor relative to the mean radar-derived R factor depending on the mean year of data origin. Data below year 1990 are calculated from state-wide averages determined from meteorological station records; year is the mean year of station records. Data above year 2000 are radar-derived R factors of entire Germany for individual years. The closed circle denotes the reference point (present map).

9. Station data are used in this study, but not to provide a direct validation of erosivity measures it seems. I would think that this could be a nice addition, i.e. to evaluate possible discrepancies between rain radar derived erosivity and station-derived erosivity.

Fig. 6 provides a direct comparison. A more detailed analysis (e.g., regional differences) seems not appropriate because the number of 33 stations and the unavoidable scatter in the data do not allow splitting the data. We also do not expect a large regional variation given the similarity between the new map and the old map (which we now provide in the Appendix). Finally, a comparison between station derived erosivities and radar derived erosivities has already been published for a large data set (115 stations and 19 944 events) by Fischer et al. (2018). In this publication, in which we neither intended to create a map nor to compare with the old map, we were not restricted to the 'Sauerborn' stations and thus could use 115 stations.

Detailed comments:

- P1L12: "for the first time". This seems incorrect as the authors also published work before that uses rain radar data to assess erosivity.

Rephrased

- P1L14: "extraordinarily large filtering"; this is a vague statement that needs rewording

We rephrased this in the Introduction and we added to the Discussion:

This pronounced stochasticity is due to the small size of convective rain cells. Just recently it has been shown by analysing radar derived rain pattern of the largest rainfall events that on average the rain amount is halved within a distance of only 2 km around the central point of a rain cell (Lochbihler et al., 2017). Given that rain amount is squared in the calculation of rain erosivity, the R factor decreases to one fourth within this distance. Larger areas can only be covered if there is movement of the rain cells. This small size of rain cells questions the use of rain gauges that only sparsely can cover space to derive rain erosivity. The inconsistent transfer functions among German states to derive erosivity from rainfall maps likely originated in the high stochasticity of rain gauge measurements under such conditions. It was only the unintended but unavoidable smoothing that was inherent in previous approaches that allowed deriving such maps. Radar technology enables us to replace this unintended smoothing by clearly defined statistical protocols and to quantify the effect of smoothing.

Lochbihler, K., Lenderink, G., Siebesma A.P.: The spatial extent of rainfall events and its relation to precipitation scaling, Geophys. Res. Lett., 44, 8629–8636 (2017). doi:10.1002/2017GL074857

- P1L15: “averaging 2001 to 2017” is not a precise statement. Probably the authors mean that the annual erosivity of 2001 to 2017 was averaged?

Changed as suggested

- P1L16 (and also L19/20): “the previous map” should be rephrased: “the erosivity map currently used in Germany, which is based on ... ”

Changed as suggested; we introduced the name “Sauerborn map” in this place to replace “the erosivity map currently used in Germany” in the following occurrences.

- P1L20: unclear: do the authors mean to say that this is based on stations that were available in 1960-1980 and continue to report until present?

We rephrased the sentence to make it clearer: “This increase in erosivity was confirmed by long-term data from rain gauge stations that were used for the previous map and which are still in operation.”

- P1L21: “by weather changes that may already be ... 1970s.” Avoid emotional wordings like “dramatic”; rather state that “but by a change in climatic conditions”.

Reworded

- P1L22: erosivity does not “fall”

Reworded

- P1L22-25: I have the feeling that this issue is a bit overstated: still the erosivity during winter months is rather small. I suppose that this requires a joint analysis with vegetation cover, which is outside the scope of this paper. Probably the main erosion on cropland would still occur during spring (in May farmers in NW-Germany have only just planted maize for example) and late summer when crops like wheat are harvested. Now it is not possible to state that “for many crops” we have “higher erosion” (P1L22) - P1L25: the “thus” and “definite” suggest a very strong causal relationship between previous statements and what is said here. I think that the authors should be more cautious; while an important input, the work cannot make definite conclusions about erosion yet.

We show (although we do this only in the discussion) that erosion under winter wheat (which is the most often grown crop in Germany) will be four-fold higher than previously expected. Practically all other crops (except clover-grass and except the system of “mulch tillage”) also pass winter in a susceptible state (which is well known; we give the reference). We do not see any exaggeration or speculation in these statements.

- P2L4-6: this is a bit vague; applied and used by whom? Does this refer to Germany or more general?

We have expanded the description of how R factor maps were usually derived in the past

- P2L29-30: I would at least shortly acknowledge existing efforts to do the same with gridded data of satellite-derived rainfall estimates.

We included two references to this method (Vrieling et al., 2010, 2014)

- P3L10-16: I feel somewhat uncomfortable with the present tense of “expect” here, given that this article is a report of a work already completed. I suggest removal, but highlighting this in the results/discussion.

These are our hypotheses (and two out of three turned out to be wrong). We replaced “expect” and the present tense by “Our hypothesis was”.

- P3L19-26: I wonder if there may be any effect of changes in the network/systems on the erosivity estimates?

We have used the RADKLIM data set that is the best estimate of precipitation based on radar- and gauge-data in Germany. A sophisticated quality control, the merging of different data sources, and a reprocessing applying one software tool lead to an at most homogenous data set, where the influence of network changes on precipitation estimates is eliminated or at least strongly reduced. However, a distinct improve in quality is detectable due to improved quality control of the raw data.

The changes in the measuring system over time were mainly intended to improve measurements where former locations had specific deficits that became apparent over time. We insofar expect the later measurement to be better, also because of the technical developments in radar technology. Furthermore, we expect that the change of the locations improves long-term averages compared to long-term averages with fixed locations because local deficits level out. These improvements have been documented for precipitation (mainly in internal reports). How much they improve erosivity calculation is unknown. An evaluation for erosivity would be rather tricky (because of the much larger variability of erosivity compared to precipitation) and of little general interest because this would mainly reflect local effects and it would only be applicable to the past. Restricting our data to the latest configuration would also not be an improvement because of the shorter time series and because the restrictions given by the latest configuration would then not be dampened by measurements with the older configuration.

We did not expand on this in the text because (i) there is too much speculation, (ii) this is a different topic that would distract from our topic

- P4L8: RW is an acronym for what?

RW is an abbreviation of **R**ADOLAN respective **R**ADKLIM and **W**eighted as it is a weighted sum of two products adjusted by different methods. We use RW only as a name but not as an acronym to indicate, which radar data were used. The data set is freely available and can be found by this name. Otherwise a lengthy explanation would become necessary. This explanation can be found in Winterrath et al. (2018), whom we cite.

Winterrath, T., Brendel, C., Hafer, M., Junghänel, T., Klameth, A., Lengfeld, K., Walawender, E., Weigl, E., Becker, A.: RADKLIM Version 2017.002: Reprocessed gauge-adjusted radar data, one-hour precipitation sums (RW) DOI: 10.5676/DWD/RADKLIM_RW_V2017.002, 2018.

- P4L25: other versions of this equation exist. See also: "van Dijk AIJM, LA Bruijnzeel, & CJ Rosewell (2002). Rainfall intensity-kinetic energy relationships: A critical literature appraisal. Journal of Hydrology 261: 1-23". Why did the authors choose for this equation?

We added a justification:

"We used the equation by Wischmeier and Smith (1978) to calculate kinetic energy although several others have also been proposed (van Dijk et al., 2002) with none being superior (Wilken et al. 2018). Our choice retained comparability with the Sauerborn map. Furthermore van Dijk et al. (2002) had shown that kinetic energy as obtained by the Wischmeier-and-Smith equation did not deviate from measured kinetic energy in Belgium neighboring Germany."

Another reason (not mentioned in the manuscript) is that the equation by Wischmeier and Smith (1978) is defined as standard among German authorities. Only recently this has been re-affirmed (DIN, 2017). An R map that is not based on the defined standard would not be used by German authorities.

DIN – Deutsches Institut für Normung: DIN 19708: 2005-02 Bodenbeschaffenheit – Ermittlung der Erosionsgefährdung von Böden durch Wasser mit Hilfe der ABAG. Beuth-Verlag, Berlin, 2017.

- P5L23: section 2.2 should be 2.3 (and also for next sections numbering should continue accordingly)

Error corrected

- P6L7/11: “neighbor” should read “neighboring”

Replaced

- P6L8: “krige” should read “kriging”

Replaced

- P6L11: “This ... pattern”. Sentence unclear.

We have expanded the sentence to better convey its message

- P6L31-32: this seems to be out of place, as it reports on results.

We added a reference to indicate that this is *a priori* knowledge (although the same was later found in our results)

- P7L12: “and the level shifts in the smooth”? I do not understand the sentence

This wording had been taken from the cited statistical reference. Now we reworded the sentence and used common language.

- P7L13: Hanning with capital H?

Changed as suggested

- P7L14-15: I think that after two reads I get the meaning, but could be formulated clearer.

Reworded and expanded

- P7L16-19: this seems to belong to results also.

We reworded this paragraph in order not to anticipate results.

- P7L26: if so, I would expect a clearer proof of this, e.g. by linking height from a DEM to erosivity, or at least show a DEM of Germany somewhere in the paper.

We added a detailed topographic map (Fig. A1 in the Appendix).

- P8, Section 3.2. I fail to clearly see a main message appearing from this section; what is the key lesson/result that the authors want to convey?

All existing erosivity maps (mostly unintendedly) employ pronounced smoothing. We explain this now in more detail in the Introduction. Due to our high data availability we were able to and had to replace the unintended and uncontrolled smoothing of existing maps by a statistical protocol because of the large small-scale spatial variability. This chapter is intended (i) to quantify the effects of this protocol, (ii) to justify the protocol and (iii) to highlight the large small-scale spatial variability that even exists for long-term averages. The third point is of particular interest because this large small-scale spatial variability of long-term averages was not known previously due to a lack in suitable data.

- P8L7: strange combination of present and past tense (smoothed). Specify that the 10-15km refer to this study.

Changed as recommended

- P8L7-9: the "disappearance" is quite logical from the description of winsorizing.

Yes; we just want to give a measure of the extent of the effect

- P8L11: "Rain erosivity from 5-min resolution data ..": it is unclear what erosivity this refers to: annual? Is this for 2011?

Reworded (and the caption of Fig. 3, to which this sentence refers, was improved)

- P8L15-16: probably this is described in methods but a bit unclear why 2011 and 2012 were chosen here.

The only reason is that this data set existed

- P9L32: "extreme" and "violent" sounds rather exaggerated. A more scientific formulation would be appreciated.

We followed the intensity classification by the UK Meteorological Office, which suggests using 'violent':

"For synoptic purposes, rain showers are classified as 'slight', 'moderate', 'heavy', or 'violent' for rates of accumulation of about 0 to 2 mm h^{-1}, 2 to 10 mm h^{-1}, 10 to 50 mm h^{-1}, or greater than 50 mm h^{-1}, respectively."

UK Met Office (2007) Fact Sheet No. 3: Water in the Atmosphere. p. 6. https://web.archive.org/web/20120114162401/http://www.metoffice.gov.uk/media/pdf/4/1/No._03_-_Water_in_the_Atmosphere.pdf

We explicitly refer to this source now.

- P10L17-18: the previous sentences compared radar-based erosivity with meteostation erosivity. Therefore I believe that this sentence makes little sense here, because there may in fact be differences because of the different data used. I more trust the fact that in P10L19 the same stations (and hopefully the same methods) were used. So please do not conclude when the previous statements do not support the conclusion yet.

There are two differences in the Sauerborn approach, first she used meteostation data and second she interpolated via a regression. In L 17-18 we exclude that the regression approach can be the reason for the difference and in L 19 we exclude that the difference in data origin (station/radar) can explain the difference. We hence need both sentences.

- P10L29-30: location is not so clear: could it be indicated in Figure 1?

We added "of the North Sea" to the sentence to make clear where the German Bight is and now we depict "German Bight" and "Baltic Sea" in the map in Fig. 1.

- P11L3-4: perhaps it is me, but I fail to fully grasp what regression was precisely done here (what against what), and with what purpose?

We reworded this sentence; furthermore we explain explicitly in the Introduction now the transfer of point R data to full maps via a regression with precipitation.

- P11L9: "trains" should be "rains"?

This was not a typo. We reworded this sentence ('tracks of thunderstorm movement') to avoid this impression.

- P11L21: see previous points also: I think that this "most pronounced changes" is overstated: the erosivity is still small.

"the most pronounced" is a relative expression; the change may be much smaller than "pronounced"; we left this wording

- P12L28-P13L2: this seems too much repetition of results to me.

We deleted this part

- P13L2: link between sentence ending with "resolutions" and sentence starting with "The pronounced" is not clear; this seems to be another topic.

- P13L3-4 I do not understand this: how can orographic rainfall increase hourly but not the peaks? And with peaks the authors refer to sub-hourly?

We deleted the sentences in L 2-4 because they were speculative anyhow

- P13L16: expected by whom? Rather "than what existing erosivity maps showed"

Reworded

- Captions should be self-explanatory: in Figure 1 I do not understand the "for a range of 128km AND the 2017 configuration". Please revise to make the caption clearer.

We are not sure what is unclear. We added '(utilized radius)' after range indicating that the radar beam does not end but signals of longer travel distances were not used and we replaced 'configuration' by 'tower locations'; note that the following parenthesis explains 'locations of some radar towers have changed over time'

- Figure 2 caption: "Erosivity map" specify in caption if this is annual average erosivity. Also units should be reported in caption.

Wording was changed and units were added.

- Figure 3: also here it should be clarified if we are looking at annual erosivity, and which years of data and why. Also why do we see a lag up to 50km? Would it make sense to make it longer? Why or why not?

Information was added

- Figure 5: caption should specify if daily erosion index (circles and blue) is from radar data.

Information was added

- Figure 6: caption should specify if Sauerborn used the exact same methods

There are likely several differences but these are not documented. E.g., at the time of Sauerborn paper, hyetographs were recorded while nowadays tipping-bucket rain gauges or weighing rain gauges are used. Sauerborn used a manual approach to identify erosive rains, their beginning, their ending and breakpoints of intensity while we used automated calculations. This was done by many and unrelated persons differing in their subjective decisions. We didn't add this because the points are many and their likely effects are unknown. The documentation is rather poor. Insofar, the new map is also a major step forward.

- Table 1: last two entries (1h winsorized and kriged) are also 17-yr? Specify. Also what years are used for annual/biannual?

We added '17-yr'

- Table A2 is probably not needed because Figure 5 is presented. If still kept, it should be organized differently so that Jan-Apr are on one page.

We left Table A2. The figure is easier for the reader (this is why it was inserted in the main body of text) while the Table is required for C factor calculations. We rearranged the table.

- Take care with wording of high/higher/low/lower: usually this refers to altitude, whereas other parameters/values are small or large.

We checked all high/low and followed the recommendations by Springer (https://www.springer.com/gp/authors-editors/journal-author/large-small-high-low/1350)

We are grateful for the careful, proficient and helpful review of our manuscript. Our replies are inserted in blue in the following.

Interactive comment on “Rain erosivity map for Germany derived from contiguous radar rain data” by Franziska K. Fischer et al.

Anonymous Referee #2
Received and published: 29 October 2018

The data were noisy so significant data treatment was applied to produce a “typical” erosivity map and an annual cycle of erosivity. The new values show greater erosivity than previously produced maps and the seasonal distribution shows an increase in winter erosivity. The main advantage of the new approach is the use of continuous data over the region.

General comments
The article is very well written, the analyses are clearly described and figures are well chosen. The results will clearly be of use.

However, some of the choices made in data treatment require further justification. My primary concern is about the level of data treatment that has been applied, which is, as the authors state, “extraordinarily large”. Because the amount of smoothing applied is indeed more than normal, it should be carefully justified.

All existing erosivity maps (mostly unintendedly) employ pronounced smoothing (presumably much stronger than we did). We explain this now in more detail in the Introduction.
Due to our high data availability we were able to and had to replace the unintended and uncontrolled smoothing of existing maps by a statistical protocol because of the large small-scale spatial variability (which was not known previously due to a lack in suitable data). In contrast to existing maps where the smoothing steps and their effects are largely unknown, we define a statistical protocol, we quantify the effects of this protocol, and we justify the protocol.
Importantly, we also provide the maps without the different smoothing steps in the Appendix and leave it to the decision of the reader, which one to use.

The aim is to produce a map of “typical” erosivity over Germany, but the erosivity distributions in time are skewed and contain outliers (from rare, extreme events) that make finding one representative value per pixel a challenge. A related problem is possible sampling effects, meaning differences between the sampled and true distribution of values (the authors mention this with respect to measurements from gauge networks that may miss entire events). The authors have applied data transformation techniques to find typical values, smooth them in space, and smooth the evolution of the average erosion index over time.

I’d like to comment on each data transformation undertaken, first to produce the per-pixel values:

1. Winsorizing:
For each pixel, the mean erosivity over 17 yearly values is taken using winsorizing. In this case the authors only replace the lowest and the highest value (with the second-lowest and second-highest respectively). How was the choice made to use winsorizing over, say, the sample median? The choice of the method used (e.g. sample median or winsorizing, and the amount of winsorizing used) should be justified – for example through the use of a density plot of erosivity values, in which the skewness will be clearly visible, to show that the final values produced are representative of “typical” values of erosivity.

From a statistical point of view a median or a geometric mean has the advantage of being more robust compared to the arithmetic mean, while the arithmetic mean has the advantage of being unbiased. From a modelling point of view, a median or a geometric mean is inacceptable because modelling individual events would then lead to a different total soils loss than modelling long-term mean soil loss using a robust estimator (due to its bias). Winsorizing was thus an (accepted) method to reduce the effect of extreme outliers (not to reduce the effect of skewness, which is an important property of erosive rains).

The effect of one-step winsorizing, which considers only the most extreme years, was already small. Using a two-step winsorising (replacing the two highest and the two lowest values) would have had an even smaller additional effect.

An acceptable alternative to our approach would have been not to use any winsorizing and kriging but to calculate arithmetic county means (on average 35 km² in size) because county means are likely used in the final application of the map (this is why we also will provide a table with county means). We decided to use the more laborious approach because we expected that would better preserve landscape features smaller than 35 km².

2. Bias-correction:
The authors state that the winsorized mean is biased for long- tailed variables. But, for skewed distributions the winsorized mean should be closer to a “typical value” of the population than the sample mean because of the removal of outlier values. So is it not the case that winsorizing produces a less biased estimate of a central tendancy than the sample mean, and the bias correction suggested by the authors undoes the benefit of the winsorizing by matching back to the (spatial) sample means which are themselves affected by outliers?

The reviewer is right that a winsorized mean should be closer to the expected long-term average. Winsorizing reduces the overweight of an extreme event (upper outlier) at a certain pixel. This reduced overweight should be balanced by reducing the underweight (lower outlier) at a second pixel in order not to cause a bias of the average. For normal distributed variable this works well while for skewed variables this balancing is not fully achieved. This is why we had to correct for the bias in order to arrive at the arithmetic average. This does, however, not cancel the effect of winsoring, because the mismatch in balancing one pixel was not put back to the same pixel but it was distributed among all 455 309 pixel. This is why the bias correction was so small (2.3%) that it could almost be neglected.

3. Ordinary kriging:
Kriging is used to fill gaps not covered by the radar data (due to beam-blocking, for example), and block kriging is used to smooth the output field. Kriging requires at least roughly symmetrically distributed input data (ideally they would be normally distributed) so that mean values are representative. It should therefore be mentioned in the article whether the distribution of “typical” values after the winsorizing procedure is symmetric, and if not whether steps have been taken to correct for this (possible options are a log transformation and/or use of the Cressie variogram estimator). Block kriging is being used in a non-standard way, as a smoother, so that each 1×1 km$_2$ pixel is estimated as the mean of values across a 10×10 km$_2$ block. How was the block size of 10×10 km$_2$ chosen?

Long-term average erosivity does not have the extreme skewness of individual events. The statistical distribution is not normal but may be multimodal because it reflects the contribution of different landscapes (mountains, plains, coastal regions etc.) to total land. The assumption of normal distribution is even more justified as we use only distances of up to 100 km (i.e., within this distance the data have to be roughly normal distributed). Furthermore, as we do only use kriging as a smoother, the weights of the data would only slightly change with a different semivariogram. A moving window presumably would have done the same job.

The block size was arbitrarily chosen. The entire smoothing steps are rather irrelevant because they do not change the pattern but only provide a slightly smoother map that makes reading easier (please compare the untreated data in Fig. A3 with the final map in in Fig. 2). We provide both maps and leave it entirely to the reader whether he prefers using the unsmoothed Fig. A3 or the smoothed Fig. 2.

After the spatial processing, the annual cycle of erosivity is calculated. Afterwards, smoothing was applied to the daily timeseries of averages. Again commenting on each step:

1. Daily erosion index:
The erosion index is calculated for each pixel and then averaged across space for each day of the year. It was not clear to me whether the pixel values used to make this average were treated in any way (kriged perhaps?) or were raw 1 km_2 values (I assume it was the raw values so that they were daily). If the distribution of daily EI values (across space for each day) is heavily skewed, then the mean of their values may not be representative (the median or a winsorized mean, for example, may be better). Was any testing for this done?

Every day was the sum of 17 yr and 455 309 pixel (i.e., n = 7.7 million). To our surprise there was this large scatter between subsequent days (indicating that 17 yr are still short and that pixel cannot replace time). We did not remove any data because a high average value with n = 7.7 million can only happen, if very many pixels at that day had a high value (i.e., erosive events occurred in many regions at the same day; this is the opposite of an outlier). The lowest value is zero and it can also not be removed because this would be the majority of all days (days without an erosive event).

The main question is whether the daily erosion index varies among landscapes. In order to analyse this, we added in the revision the daily erosion index for the SE, SW, NE and NW quadrant of Germany. These four quadrants differ in climatological properties (e.g., continentality; annual rainfall and altitude) but the resulting pattern was identical for all quadrants (correlation between them yielded $r^2 > 0.998$) indicating a stability of the seasonal pattern. This close correlation also indicates that the influence of outliers is small.

2. 13-day centred median, 3-day skip mean, and 25-day centred hanning mean:
This choice of smoothing routines needs to be better justified. Why was this combination of window sizes (13, 3, and 25 day) and operators chosen, and how was it judged whether the smoothed values represented the true signal? As a suggestion that may provide more information to the reader: the authors could consider displaying maps not only of winsorized mean of annual values, but also per- pixel median, 10th percentile, and 90th percentile, to show not only “typical” values but maps of extreme erosivity values as well, and to show the spread of values for each pixel.

We added a paragraph on smoothing in the Introduction.

In short, the statistical recommendation is to use smoothing until the information can be seen that is intended to be shown. This recommendation may unsatisfactory for the inexperienced and appears arbitrary. However, there cannot be a statistical criterion because the degree of required smoothing depends on the intended application, which is outside statistics.

We could have used a cumulative density function (cdf) instead of a probability density function (pdf) to describe seasonality. This would have required no smoothing at all but with the cdf it would have been more difficult for the user to assess the effect of different crop management options. The cdf of the unsmoothed data correlates with the cdf of the smoothed data with $r^2=0.9998$ (n=365), proofing that smoothing has not caused any relevant change in seasonality. We added to the manuscript:

“Despite the strong smoothing that was necessary for the probability density function, the smoothing did not change the cumulative density function (which is used for calculating C factors). The cumulative density functions of the original data and of the smoothed data correlated with $r^2=0.9998$ (n=365).”

The window sizes are typically used values. A median with n=2 would produce an arithmetic mean. The advantage of the median filter compared to the arithmetic mean increases with increasing window size. At a window size of n=365 identical values for all days would result and the seasonality would be completely destroyed. A window size of n=13, which is also about the time window of individual crop management practices, ascertains that the seasonality is maintained. A skip mean is always applied with n=3. For the hanning mean a similar reasoning can be put forward as for the median filter. Due to the decreasing weights, the window size can be somewhat larger than for the median filter and window size has less influence (even for n=365 some seasonality would be retained). Also the order of the filters is quasi standard. A median filter only makes sense if it is applied in first place. After some averaging has occurred, the median filter loses its advantage compared to the arithmetic mean and both would produce very similar values. The skip mean cannot be the last filter because it distributes a high (or low) value completely to its neighbours and a high (or low) value is replaced by the low (or high) values of the neighbours. The skip mean thus inverts the pattern within the window size of n=3. Hence, it has to be followed by some averaging, which puts the high (or low) value back in place because during averaging some information is inherited from the neighbours on both sides. The hanning mean is especially versatile in this case because the weights (or the window size) allow adjusting to some degree how much of the high (or low) values is put back in place and how much is left with the neighbours.

Again, the statistical treatment is not critical because we also display the original data. The reader can decide whether he likes our smoothing or not. He may draw his own line where he thinks that the line should be (this is how it was done by Wischmeier and Smith, 1978, and still by Rogler and Schwertmann, 1981).

Specific comments

1. Page 2, line 24–25: “Unstable and unreliable transfer functions result that differ pronouncedly” – I do not understand the sentence, could you please rephrase?

Rephrased

2. Page 2, line 30: Please include a general reference for the radar measurement principle. One such reference could be the book by Bringi and Chandrasekar (2001), Polarimetric Doppler Weather Radar, Cambridge Uni. Press.

Thank you for the suggestion. To put this into the European context, we additionally cite:

Meischner, P., Collier, C., Illingworth, A., Joss, J., Randeu W.: Advanced weather radar systems in Europe: The COST 75 action, Bull. Amer. Meteorol. Soc., 78, 1411-1430, 1997.

3. Page 3, line 12: I see your point that the use of continuous radar data avoids missing large and rare events that could be missed completely by gauge networks. But you do a lot of processing to the radar data, including winsorizing and smoothing, which reduces the influence of rare extreme events on the summary statistics. There are two separate problems here: sampling (gauges may miss an event) and then what value to use as a “typical” value for a skewed distribution. It is important that justifications for the data treatment show that the chosen “typical” measure is appropriate.

We fully agree. This is why we examine in detail the effects of the different statistical steps during smoothing. Now we also provide in the Introduction an overview over the previously used, unintended and uncontrolled steps of data manipulation that were necessary to arrive from gauge data at erosivity maps. The origin of the problem, however, rests in the characteristics of erosive events and can thus not be avoided. The use of contiguous radar data allows replacing several poorly controlled steps by clearly defined statistical methods, which is a major step forward but certainly better methods will be found in future the better we understand the origin of variation, the more data are gathered and the better the computing methods will become.

4. Page 3, line 31: Which Z-R relationship is used?

We provide a reference now

5. Page 4, line 6: Is the figure of 1 gauge per 80 km^2 an average value?

Yes; we added “equivalent to” to make clear that this density is calculated from the number of 4000 stations per Germany

6. Page 4, line 20: For clarity, it would be helpful to include the units of Imax30 and Ekin when the variables are introduced here; this is especially important because Ekin [kJ m^{-2}] and $Ekin_{,i}$ [kJ m^{-2} mm^{-1}] have different units.

We included the units when the variables were introduced

7. Page 4, line 24: You should reference Fischer et al 2018 (from your references list) here since your definitions, units, and descriptions are very similar to those used in your previous paper.

We cite Rogler and Schwertmann (1981) now because they were the first who transferred the Wischmeier equations in US units to SI units.

8. Page 4, line 29: “the R_e sum” – do you mean “the sum of R_e”?

Yes; we rephrased the sentence

9. Page 5, lines 14–15: For a given pixel, if too many years were excluded then the sampling may become less representative. How often were pixels affected by this exclusion of years, and were there pixels for which many years were excluded?

The requested information had already been given ("If the effective number of excluded years was larger than one, the respective pixel was excluded. This was the case for 0.6% of all pixels.") but now we moved it to a different place where it may be expected more by the reader.

This loss of years mainly occurred in marginal regions in the very North or very South that had only been captured by radar data before or after the displacement of radar sites (e.g. in the far North due to the shift of the radar Hamburg to Boostedt in 2014).

10. Page 5, lines 16–22: "replaced by the maximum 1-h rain depth" - should this read rain intensity?

Usually rainfall is reported for a certain period of time (per day/month/year) and hence this should always be called intensity instead of depth. However, depth is commonly used if longer periods of time (days, years) are considered during which short-term intensity varies.

We replaced "depth" by "intensity".

11. Page 5, lines 16–22: As I understand it, the scaling factors are being used to adjust the method of calculating erosivity to put a "virtual rain gauge" in each radar pixel, to account for the fact that radar measurements are areal and integrated over time and therefore smooth out rainfall intensity peaks. Since rain intensity depends on temporal resolution, and you require 30 minute maximum rain rates which would be smoothed by the use of 1 hour radar data, I see why a temporal scaling factor could be used. But spatially, the areal measurements at 1 km^2 resolution can be assumed to be representative of each 1 km^2 pixel, and since you are producing erosivity values at the same resolution, I don't understand why a spatial scaling factor (or indeed the method scaling factor) is required. Please could you explain more here why the scaling factors are used and how they are applied (e.g. it is not clear which threshold is lowered to 5.8 mm h^{-1}).

We agree that this is difficult to understand. We had to dedicate an entire publication to this tricky question (Fischer et al., 2018). An additional explanation with one or two sentences in this manuscript would open more questions that it would answer. We prefer to leave it like this.

In the discussion we now explain (and cite a reference) that rain erosivity on average drops to one fourth at only 2 km distance from the centre of a convective rain cell. This pronounced patchiness requires a spatial scaling factor.

We repeated "Imax30" in this sentence to make clear, which threshold had to be adjusted.

12. Page 6, line 14: The use of some independent data to test the spatial representativity of the smoothed data is a good idea, but is this test data independent? It is also based on radar data. Has the test region data been compared to gauges or other ground truth data to ensure it is accurate?

In this case we only wanted to examine the effects of our data treatment but not the comparison between radar-derived and gauge-derived erosivities. We have done this extensively in Fischer et al. (2018), which we cite. In this publication we compared 19 944 events observed at 115 stations with radar-derived erosivities for the same location.

13. Page 7, lines 1–2: “The cumulative distribution curve for the test region calculated from 5-min data will then be a fair estimate of the return periods anywhere in the research area” – I do not think this is proven. Even if the test region and the whole area agree at 1 hour resolution, extreme intensities are smoothed out at this lower resolution, so it does not necessarily follow that the 5 minute cumulative distributions are the same across all regions.

We weakened the statement:

“The cumulative distribution curve for the test region was also calculated using the 5-min rain data. Given that the cumulative distribution curves of the entire study area and the test region agree for the relative erosivities calculated from 1-h data, we expect that the relative erosivities calculated from 5-min rain data of the test region can serve as a first estimate for the entire study region.”

14. Page 7, lines 19–20: Please include a reference for these statements about radar accuracy (they are correct but require a citation).

We added a reference

15. Section 3.1: I suggest that to back up your observation that the regional pattern in erosivity is dominated by orography, you should include a topographic map showing ground elevation for comparison with the map in Figure 2.

We added a detailed topographic map in the Appendix

16. Page 8, line 13: “Using the normal distribution” – but are the erosivity values normally distributed?

This is clearly not the case although long-term average erosivity does not have the extreme skewness of individual events or the skewness of individual years. The statistical distribution is not normal but may be multimodal because it reflects the contribution of different landscapes (mountains, plains, coastal regions etc.) to total land. The assumption of a normal distribution is only used here for illustration purposes to “translate” the semivariance, which may be difficult to grasp by some readers, to the ordinary R factor space. This assumption has no further relevance for our analysis. We deleted this phrase.

17. Page 8, line 32: Which variogram was the kriging conditioned by? I would expect kriging to maintain the spatial stucture even in a block kriging case, so it is odd that the kriging changes the variogram.

The semivariogram used for kriging is indicated as “1 h, 17 yr” in Fig. 3. We added a numbering to the semivariograms in Fig. 3 so that we can clearly refer to each of the semivariograms in the text.

The semivariogram after kriging always differs from the semivariogram before kriging because at least the nugget effect is removed by kriging. Block kriging will additionally remove any pattern that is smaller than the block size. It can then not appear anymore in the semivariogram after kriging. This is a well-known phenomenon in geostatistics and usually addressed as change of support or as regularization or as modifiable areal unit problem. Such a change of support may even turn a spherical model into a Gaussian model. See for instance:

Clark I.: Regularization of a semivariogram, Computers & Geosciences, 3, 341-346, 1977.

Gotway, C.A., Young, L.J.: Combining incompatible spatial data, J. Amer. Statistical Assoc., 97, 632-648, 2002.

Emery, X.: On some consistency conditions for geostatistical change-of-support models, Mathematical Geology, 39, 205-223, 2007.

18. Section 3.3: I suggest adding more lines to your Figure 4 to show all the lines you mention in the text.

We do not understand this comment. In the text we mention return periods of 2 yr, 30 yr and 100 yr. In Fig. 4 we show lines indicating return periods of 2 yr, 5 yr, 10 yr, 30 yr and 100 yr.

19. Page 9, line 21: I'm surprised that you would expect less than the mean erosivity for an event with a return period of 2 years. Any comment there?

This is due to the fact that total erosivity is determined by extreme events. To illustrate this: the largest event recorded by Fischer et al (2018) during only two months was 1270 N h^{-1}. This means that if at that location no other erosive rain would fall during the next 10 yr, the average annual rain erosivity would still be the same as that of all other locations.

20. Page 9, line 27: "d" is presumably for days but should be spelled out.

This would not comply with the recommendations of NIST and other institutions of standards, which require that unit symbols and unit names must not be mixed.

Thompson, A., Taylor, B.N., Guide for the Use of the International System of Units (SI), NIST Special Publication 811, 2008

21. Page 9, line 32: To see exactly what is going on here, did you compare the distributions of erosivity values for each of these example days? I suspect that the median values would be more stable.

The value was calculated as the accumulated erosivity of an individual day over 17 yr and all pixels divided by the accumulated erosivity over all days and all pixels during 17 yr. Hence there was only one value for each day. Calculating the erosivity index individually for each year and each pixel would yield a (very stable) median of zero for all days (because there are only about 20 events per year at a location).

What was surprising to us was the fact that despite this huge sample size for every day (almost 8 million pixel days), the values still differed so much for consecutive days. This is because averaging over years cannot be replaced by averaging over locations. During some days many locations (pixels) received erosive rainfall while on the next day the weather system may have changed and no pixel receive erosive rain. It is clear that with 20 events per year and 17 years (=340 events per pixel) some days must exist in each pixel that cannot have received an event even if the events would be evenly distributed.

22. Page 10, line 20: I think Fig. 5 should be Fig. 6.

We corrected the typo

23. Page 11, line 18: No definition of C-factor calculations is given; please add one.

We added a reference here. A short description was already given in the Introduction

24. Page 12, line 22: Please define (R)USLE.

RUSLE is explained in the Introduction now

25. Figures 2, A1, and A2: Units for the plotted variable should be stated either in the key or caption.

Information was added

Technical corrections

• Page 5, line 19: The word "occurred" can be removed.

Sentence was rephrased

• Page 7, line 12: By "in the smooth" do you mean "in the smoothing operation"?

This wording had been taken from the cited statistical reference. Now we reworded the sentence and used common language.

• Figure 2: In the caption the average sizes of the local authority and community areas should be areas (km^2).

Changed as requested

• Page 8, line 8: "very extreme" is redundant when "extreme" will do.

Changed as requested

• Page 9, line 23: "extremer" should be replaced by "more extreme".

Changed as requested

Rain erosivity map for Germany derived from contiguous radar rain data

Franziska K. Fischer[1,2,3], Tanja Winterrath[4], Karl Auerswald[1]

[1]Technische Universität München, Lehrstuhl für Grünlandlehre, Freising, 85354, Germany
[2]Bayerische Landesanstalt für Landwirtschaft, Freising, 85354, Germany
[3]Deutscher Wetterdienst, Außenstelle Weihenstephan, Freising, 85354, Germany
[4]Deutscher Wetterdienst, Department of Hydrometeorology, Offenbach/ Main, 63067, Germany

Correspondence to: Karl Auerswald (auerswald@wzw.tum.de)

Abstract. Erosive rainfall varies pronouncedly in time and space. Severe events are often restricted to a few square kilometers. R~~ain r~~adar rain data with high spatio-temporal resolution enable this pattern of erosivity to be portrayed ~~for the first time~~with high detail. We used radar data ~~collected~~ with a spatial resolution of 1 km² ~~for~~ over 452 503 km² to derive a new erosivity map for Germany and to analyze the seasonal distribution of erosivity. ~~Extraordinarily large filtering was necessary to extract~~ T~~t~~he expected long-term regional pattern was extracted from the scattered pattern of events by several steps of smoothing.~~. Filtering~~ This included averaging erosivity from 2001 to 2017 and smoothing in time and space. The pattern of the resulting map was predominantly shaped by orography. It generally agrees~~d~~ well with the erosivity ~~previous~~ map currently used in Germany (“Sauerborn map”), which is~~on~~ based on regressions ~~of~~ using rain gauge data (mainly from the 1960s to 1980s). ~~The pattern was predominantly shaped by orography. However, the new map has more detail; it deviates i~~In some regions the pattern of both maps deviates because~~ where~~ the regressions ~~previously~~ of the Sauerborn map~~used~~ were weak~~;~~. ~~m~~Most importantly, ~~it~~ the new map shows that erosivity is about 66 % ~~higher~~larger than in the Sauerborn map~~ previously used~~. This increase in erosivity was confirmed by long-term data from rain gauge stations that were used for the ~~previous~~ Sauerborn map and which are still in operation. The change was thus not caused by using a different methodology but by ~~weather~~ climate change~~s~~ ~~that may already be a dramatic result of climate change~~ since the 1970s. Furthermore, the seasonal distribution of erosivity ~~showed~~ shows ~~that more erosivity falls during the~~a slight shift towards the winter period when soil cover by plants is usually poor. This shift in addition to the increase of erosivity may have caused an increase of erosion for many crops. For winter wheat, predicted soil erosion is therefore now about four times larger than in the 1970s~~For many crops higher erosion therefore also results from the change in seasonality. Predicted soil erosion in winter wheat is now about four times higher than in the 1970s due to the seasonal changes, combined with the increased erosivity~~. These highly resolved topical erosivity data ~~with high spatial resolution~~ will thus have definite consequences for agricultural advisory services, landscape planning and even political decisions.

1 Introduction

Soil erosion by heavy rain is regarded as the largest threat to the soil resource. Rain erosivity~~, which~~ is a rain's ability to detach soil particles and provide transport by runoff~~,~~ and thereby is one of the factors influencing soil erosion. The most commonly used measure of rain erosivity is the R factor ~~from~~ of the Universal Soil Loss Equation USLE (Wischmeier, 1959; Wischmeier and Smith, 1958, 1978) or the Revised Universal Soil Loss Equation RUSLE (Renard et al., 1991), although other concepts also exist (Morgan et al., 1999; Schmidt, 1991; Williams and Berndt, 1977). The R factor is given as the product of a rain event's kinetic energy and its maximum 30 ~~-~~min intensity. Both components are usually derived from hyetographs recorded by rain gauges. Such rain gauge data are spatially scarce. For instance, in Germany only one rain gauge per 2571 km² was available for the currently used R map ~~currently in use~~ (Sauerborn, 1994; this map will be called “Sauerborn map” in the following). Hence, point information has to be spatially interpolated to derive an R map that enables ~~R~~ to ~~be~~ estimate~~d~~ R for any location. Different interpolation techniques have been applied. Most often ~~C~~correlations (transfer functions) of R with~~to~~ other meteorological data available at higher spatial density were used ~~the most~~ (for an overview see Nearing et al., 2017). The ~~German R-factor~~Sauerborn map ~~is~~ was based on correlations between R and normal-period summer rain depth~~fall~~ or normal-period annual rain depth~~fall~~, which differ~~ing~~ between federal states (Rogler and Schwertmann, 1981; Sauerborn, 1994, and citations therein).

Recent research has shown that the erosivity of single events exhibits ~~enormous~~ strong spatial gradients~~ in space~~ (Fiener and Auerswald, 2009; Fischer et al., 2016; Fischer et al., 2018b; Krajewski et al., 2003; Pedersen et al., 2010; Peleg et al., 2016).~~, which~~ This is due to the small spatial extent of convective rain cells which is typical for erosive rains. The resulting heterogeneity has two consequences. First, interpolation of erosivity between two neighboring rain stations will not be possible for individual rains because a rain cell in between may be completely missed. Second, even long records of rain gauge data may miss the largest events that occurred in close proximity to a rain gauge and thus underestimate rain erosivity. This is illustrated nicely by the data of Fischer et al. (2018b). They showed that the largest event erosivity, which was recorded by contiguous measurements over only two months, was more than twice as large as the largest erosivity ~~that occurred during 16 years when the same area was covered by 115 rain gauges~~recorded by 115 rain gauges over 16 years and the same area. Furthermore, this single event contributed about 20 times as much erosivity as the expected long-term average. Even in a 100-yr record this single event would thus still change the long-term average erosivity. The large variability of erosivity in space and time then directly translates to soil loss. This may be illustrated by soil loss measurements in vineyards in Germany. Emde (1992) found a mean soil loss of 151 t ha^{-1} yr^{-1} averaged over 10 plot years while Richter (1991) only measured 0.2 t ha^{-1} yr^{-1}, averaged over 144 plot years. The difference is due to the largest event during the study by Emde (1992), which obviously had too much influence on the mean compared to the size of his data set. Such an event was missing entirely in Richter's (1991) much larger data set. The inclusion of rare events when measured by chance by a rain gauge leads to statistical problems due to their extraordinary magnitude. They cause outliers in regression analysis ~~Unstable~~ and ~~unreliable~~ thus strongly affect transfer functions.~~ result that differ pronouncedly depending on whether~~

~~a large event is included or not.~~ To avoid an effect by single events to the transfer function ~~this~~, Rogler and Schwertmann (1981) excluded all events for which the estimated return period was more than 30 yr (assuming that event erosivities followed a Gumble distribution)~~., prior to the development of their transfer function.~~ In consequence, the largest event was replaced by zero and erosivity and, in turn, soil erosion was underestimated ~~This approach must underestimate erosivity and, in turn, soil erosion because the largest events are then replaced by zero~~.

The demand for contiguous rain data to create R-factor maps ~~has~~ was only recently ~~been able to be~~ met by satellite data (Vrieling et al., 2010, 2014) and by radar rain data with considerably larger spatial (presently up to 9-fold) and temporal resolution (presently up to 36-fold) ~~radar rain data of high spatial and temporal resolution~~(Fischer et al., 2016). Put simply, the measurements are based on the principle that radar beams are reflected by hydrometeors (Bringi and Chandrasekar, 2001; Meischner et al., 1997). The intensity of the reflection depends on rain intensity and the travel time of the reflected radar beam depends on the distance between the emitting and receiving radar tower and the hydrometeor. Radars usually measure with a resolution of approx. 1° azimuth and 125 to 250 m in the direction of beam propagation. The data are then typically transformed to grids of square pixels of 1 km² (Bartels et al., 2004; Fairman et al., 2015), 4 km² (Koistinen and Michelson, 2002; Michelson et al., 2010) or 16 km² (Hardegree et al., 2008) after many refinement steps.

An R factor (map) can serve two purposes with contrasting requirements. First, it can be used in combination with measured soil loss or reported damages (e.g., Mutchler and Carter, 1983; Vaezi et al., 2017; Fischer et al., 2018a). In this hindcast case, highest possible spatial and temporal resolution is recommendable. The second application of the R factor is for forecasting erosion which is required, e.g., for field use planning (Wischmeier and Smith, 1978). In this case, the long-term expectation is of interest rather than the true R factor of the (near) past that was influenced by the stochastic location of individual rain cells. Thus, for future modelling, smoothing of the stochastic noise is necessary.

Also the existing R maps are based on a number of smoothing steps, which were rather uncontrolled and of unknown degree. Most R maps use regressions between long-term averages of erosivity and long-term meteorological parameters, e.g. annual rain depth. For long-term averages, periods of more than 20 years are accepted (Chow, 1953; Wischmeier and Smith, 1978) to remove the stochasticity of individual events and leave the general pattern. In consequence, a temporal smoothing follows from using long-term averages and a spatial smoothing follows from the transfer functions and their application to rainfall maps. These rainfall maps include a third step of smoothing because the meteorological recommendation is to use normal-period rainfall (30 yr) data and point data (meteorological stations) have to be extended to create a map. For example for the R map in Germany (Rogler and Schwertmann, 1981), the precipitation map of 1931 to 1960 was used which was the last available normal-period. This precipitation map was mainly based on educated guesses of the best meteorologists at that time as geostatistical tools existed not yet.

With the large increase in data availability by radar measurements and the development of (geostatistical) smoothing tools this uncontrolled smoothing can be replaced by accepted statistical methods of smoothing. The general recommendation is to apply smoothing until the pattern can be seen that is intended to be shown (O'Haver, 2018; Simonov, 1996; Quantitative Decisions, 2004) by using several smoothing steps in sequence (O'Haver, 2018; Wedin et al., 2008). The most reliable reconstruction seeks the simplest underlying image consistent with the input data (Puetter et al., 2005). We will thus use a set of different spatial and temporal smoothing functions in combination and we will quantify how much noise is removed by the individual functions and we provide the unsmoothed maps in the Appendix for comparison.

In this study, we used the new RW product from the radar climatology RADKLIM (RADar KLIMatologie) from the German Meteorological Service (Deutscher Wetterdienst, DWD). RW data provide gauge-adjusted and further refined precipitation for a pixel size of 1 x 1 km² (Winterrath et al., 2017, 2018). RW data of 17 yr (2001 – 2017) ~~are~~ were available as a contiguous source of rain information. Using these data to establish a new R-factor map for Germany should be a major step forward compared to the ~~existing~~ Sauerborn map, which was derived from an inconsistent set of data compiled by different researchers (e.g., some had winter precipitation data available and used it while others did not; see Sauerborn, 1994) and with equations developed independently for 16 federal states. Our data set is much larger (by a factor of 2571 regarding locations) and, because of the contiguous data source, it does not require interpolation with transfer functions. ~~We expect~~Our first hypothesis was that there will be considerable changes in the pattern of erosivity due to the removal of transfer-function weaknesses. Our second hypothesis was ~~We also expect~~ that the R-factor map will exhibit ~~higher~~larger values than the ~~existing~~ Sauerborn map, for two reasons. Very large and rare events will no longer be missed, as occurred previously due to the large distances between meteorological stations, and there is no longer any need to remove these events to arrive at robust transfer functions. The second reason for ~~higher~~larger R factors is due to global climate change, as Rogler and Schwertmann (1981) and Sauerborn (1994) mostly used data from the 1960s, 1970s and 1980s. Global climate change is expected to increase rain erosivity (Burt et al., 2016).

2 Material and methods

2.1 Radar-~~based~~ derived precipitation data

DWD runs a Germany-wide network of presently 17 C-band Doppler radar systems (Fig. 1). This network underwent several upgrades during the analysis period. At the start of the time period considered, five single-polarization systems (DWSR-88C, AeroBase Group Inc., Manassas, USA) were operated without a Doppler filter, the latter being added between 2001 and 2004. Between 2009 and 2017, DWD replaced the network of C-band single-polarization systems of the types METEOR 360 AC (Gematronik, Neuss, Germany) and DWSR-2501 (Enterprise Electronics Corporation, Enterprise, USA) with modern dual-polarization C-band systems of the type DWSR-5001C/SDP-CE (Enterprise Electronics Corporation), all equipped with Doppler filters. During this period, a portable interim radar system of the type DWSR-5001C was installed at some sites.

The radar systems permanently scan the atmosphere to detect precipitation signals. Every five minutes, the radars perform a precipitation scan, each with terrain-following elevation angle to measure precipitation near the ground. The resulting local reflectivity information over a range of 128 km is combined to form a Germany-wide mosaic of about 1100 km in the north-south and 900 km in the west-east direction. The reflectivity information is converted to precipitation rates applying a reflectivity–rain rate (ZR) relationship (Bartels et al., 2004). An operational quality control system screens the radar data. To further improve the quantitative precipitation estimates, the radar-derived precipitation rates are summed to hourly totals and immediately adjusted to gauge data from more than 1000 meteorological stations resulting in RADOLAN (RADar OnLine ANeichung, i.e. online-adjusted, radar-derived precipitation), which provides precipitation data in real time, mainly for applications in flood forecasting and flood protection (Bartels et al., 2004; Winterrath et al., 2012).

Based on RADOLAN, the climate version RADKLIM is derived. Compared to the real-time approach, the data are additionally offline-adjusted to daily gauge data, combining a total of more than 4400 rain gauges measuring hourly and daily (equivalent to 1 rain gauge per 80 km²). The data are then reprocessed by new climatological correction methods, e.g. for spokes, clutter or short data gaps. Spokes result from permanent obstacles blocking the radar beam, while clutter is introduced by non-meteorological targets like windmills or birds. The final product (called RW data) has a temporal resolution of 1 h and a spatial resolution of 1 km x 1 km in polarstereographic projection. For more detailed information on RADKLIM the reader is referred to Winterrath et al. (2017). The RW data, restricted to the German territory, are freely available (Winterrath et al., 2018). For the first time, the RADKLIM data set provides contiguous precipitation data with high temporal and spatial resolution. It includes local heavy or violent precipitation events (for classification of heavy and violent see UK Met Office, 2007) that are partly missed by point measurements alone. Thus, it particularly improves the analysis of extreme precipitation events.

Two additional data sets were used to verify the validity of the approach and to examine effects of methodological details (see below). These data sets are erosivities derived from radar data at 5 ~~-~~min resolution taken from Fischer et al. (2016) and erosivities derived from rain-gauge data of 115 stations in Germany from 2001 to 2016, which were taken from Fischer et al. (2018b).

2.2 Erosivity calculation procedure

According to Wischmeier (Wischmeier, 1959; Wischmeier and Smith, 1958, 1978), the erosivity of a single rain event (R_e in N h^{-1}) is the product of the maximum 30 ~~-~~min rain intensity (I_{max30} in mm h^{-1}) and the total kinetic energy per unit area (E_{kin} in kJ m^{-2}). ~~For hyetographs recorded by rain gauges, an erosive rain event is defined as a total precipitation amount (P) of at least 12.7 mm or an I_{max30} of more than 12.7 mm h^{-1} that is separated from the next rain by at least six hours.~~

$$R_e = I_{max30} * E_{kin} \tag{1}$$

An erosive rain event is defined to have at least a total precipitation amount (P in mm) of 12.7 mm or an I_{max30} of more than 12.7 mm h^{-1} that is separated from the next rain by at least six hours. In order to scan and fulfil the 6 h citerion, we did not separate between days but used a continuous 17 yr data stream. Specific ~~K~~kinetic energy $e_{kin,i}$ per mm rain depth (in kJ m^{-2} mm^{-1}) is given for intervals i of constant rain intensity I (in SI units according to Rogler and Schwertmann, 1981):

For 0.05 mm h^{-1} $\leq I <$ 76.2 mm h^{-1}:

$$e_{kin,i} = (11.89 + 8.73 * log_{10} I) * 10^{-3} \tag{2.1}$$

For $I <$ 0.05 mm h^{-1}:

$$e_{kin,i} = 0 \tag{2.2}$$

For $I \geq 76.2$ mm h^{-1}:

$$e_{kin,i} = 28.33 * 10^{-3} \tag{2.3}$$

We used the equation by Wischmeier and Smith (1978) to calculate specific kinetic energy although several others have also been proposed (van Dijk et al., 2002) with none being superior (Wilken et al., 2018). Our choice retained comparability with the Sauerborn map. Furthermore van Dijk et al. (2002) had shown that kinetic energy as obtained by the Wischmeier-and-Smith equation did not deviate from measured kinetic energy in Belgium neighboring Germany.

For all intervals i, $e_{\mathrm{kin},i}$ is multiplied with the rain amount of this interval and then summed to yield E_{kin} for the entire event. The annual erosivity of a specific year is the sum of R_e of all erosive events within this year. The average annual erosivity (R) is then the average of all annual erosivities during the study period (17 yr in this case). While in the USA and other countries the unit MJ mm ha^{-1} h^{-1} is often used for R_e, we use N h^{-1} because it is the unit most often used in Europe and because of its simplicity. Both units can be easily converted by multiplying the values in N h^{-1} with a factor of 10 to yield MJ mm ha^{-1} h^{-1}. The unit for R is then N h^{-1} yr^{-1}.

Rain erosivity strongly depends on intensity peaks. Fischer et al. (2018b) have shown that these peaks increasingly disappear the lower the spatial and temporal resolution becomes. This can be accounted for by scaling factors but these scaling factors can only adjust to an average behavior, while ~~the influence of the true event R_e~~ the factors may either be too large or too small for a specific event. A high spatio-temporal resolution should be used to determine R_e for individual events. ~~To~~ This is not required to determine the long-term average pattern like an~~, i.e. an~~ R-factor map for planning and prediction purposes. In that case~~, using~~ data with lower resolution and ~~applying~~ the application of appropriate scaling factors is advantageous because this will reduce the noise introduced by large events of small spatial extent that would not be leveled out by averaging alone. We will use data in 1 ~~-~~h time increments~~, which additionally have the advantages that they~~ as those are adjusted to rain gauge measurements and the amount of data is reduced by a factor of 12 compared to 5 ~~-~~min increments. This is especially important when all calculations, including identification of rain breaks > 6 h and periods of I_{max30}, have to be carried out for many years and many locations. In our case, roughly 7×10^{10} 1 ~~-~~h increments had to be processed.

~~Gaps in the time series have been considered when calculating mean R factors by scaling the total sum of erosivity over the whole time series to 365.25 days. If the effective number of missing values exceeded two months per year, the respective year was excluded from the calculation for that pixel.~~

According to Fischer et al. (2018b), the following modifications in the calculation of R_e had to be made to account for the temporal resolution of 1 h, the spatial resolution of 1 km² and the method of measuring rain by radar: (i) I_{max30} was replaced by the maximum 1 h rain ~~depth~~ intensity and the threshold for I_{max30} was lowered to 5.8 mm h^{-1}, while the total precipitation threshold remained at 12.7 mm. (ii) ~~Rain breaks separated events when f~~Five or more subsequent 1 h intervals without rain separated events~~occurred~~. This assumed that rain events stop and start on average in the middle of the first and the last non-zero rain interval, yielding a total rain break of at least 6 h. (iii) The temporal scaling factor was 1.9 and the spatial scaling factor was 1.13, to which 0.35 ~~has~~ had to be added to account for the radar measurement instead of the rain gauge measurement. The total scaling factor [(1.13 + 0.35) × 1.9] was then 2.81.

Gaps in the time series were considered when calculating annual sums of erosivity by scaling the total sum of erosivity over the whole time series to 365.25 days. If the effective number of missing values exceeded two months per year, the respective year was excluded from the calculation for that pixel. If the effective number of excluded years was larger than one, the respective pixel was excluded. This was the case for 0.6 % of all pixels.

2.~~2~~3 Steps to ~~G~~generate~~ing~~ an ~~Germany-wide~~ R-factor map

The reduction of noise by using a 17 yr mean and 1 ~~-~~h increments was still not sufficient to level out the most extreme events. Two further ~~filters~~smoothing steps were therefore applied~~, in addition to using a 17-yr mean~~. The first ~~averaging~~ step was to winsorize the annual erosivities of the 17 yr for each individual pixel by replacing the lowest value with the second-lowest value and the highest value with the second-highest value (Dixon and Yuen, 1974). Winsorizing is an appropriate measure for calculating a robust estimator of the mean in symmetrically distributed data but it is biased for long-tailed variables like rain erosivity. Thus, the country-wide mean of all winsorized data (94~~6~~ $\mathrm{N\,h^{-1}\,yr^{-1}}$) was ~~lower~~ smaller than the mean of the original data (96~~8~~ $\mathrm{N\,h^{-1}\,yr^{-1}}$). In order to remove this bias, we binned all data in 26 bins of 20 $\mathrm{N\,h^{-1}\,yr^{-1}}$ width and calculated the mean R before and after winsorizing. For bins with $R < 180$ $\mathrm{N\,h^{-1}\,yr^{-1}}$, comprising 95 % of all pixels, the bias increased linearly with R ($r^2 = 0.92$; $n = 8$) and amounted to 2.3 % of R. Above 180 $\mathrm{N\,h^{-1}\,yr^{-1}}$ there was no further increase in the bias ($r^2 = 0.01$, $n = 18$), which was, on average, 3.4 $\mathrm{N\,h^{-1}\,yr^{-1}}$. We removed the bias by adding 2.3 % to all values < 180 $\mathrm{N\,h^{-1}\,yr^{-1}}$ and 3.4 $\mathrm{N\,h^{-1}\,yr^{-1}}$ to all values above.

The ~~third noise reduction step~~last smoothing step applied geostatistical methods. A semivariogram (over a range of 50 km) was calculated and ordinary kriging was applied. Geostatistical analysis was done ~~in~~ using the program R (version 3.5.0; R Core Team, 2018) ~~using~~ and gstat (Gräler et al., 2016). ~~To remove noise, a~~A block size of 10 × 10 km² was chosen to remove noise and to fill the pixels with data gaps, while the spatial resolution remained at 1 km~~ to remove noise and~~ ~~. This step was also necessary to fill pixels with data gaps of more than one year (0.6% of the entire area)~~. The missing information was obtained from neighboring pixels. The radar data ~~extended beyond~~outreached German borders. In total, 452 503 pixels were used to ensure ~~low~~small ~~krige errors~~kriging variances near borders or on islands, while the final map was restricted to the German land surface (357 779 pixels).

Using 1 ~~-~~h data instead of 5 ~~-~~min data reduced the effect of single extreme events at certain locations. Winsorizing reduced the effect of extreme years at a location, in addition to the effect of averaging 17 yr. Finally, kriging used the information from neighboring pixels to reduce the effect of the extremes. This ~~should not have~~smooths among near neighbors (distance <20 km) but does not affect~~ed~~ the regional pattern (>20 km). To evaluate whether this was the case and to quantify the effect of all smoothing steps, we used the data from Fischer et al. (2016~~),~~). ~~who~~ They had calculated rain erosivity from 5 ~~-~~min-resolution radar data for two years (2011 and 2012) and an area of 14 358 km² (yielding a total of 28 770 pixel years), which is called “test region” in the following. Using these data we calculated semivariograms ~~after each smoothing step~~ from annual to biennial erosivities based on 5 ~~-~~min and 1 ~~-~~h resolution. ~~,~~These semivariograms were compared to those from ~~for~~ 17~~-~~ yr average erosivities, ~~for~~ 17 yr winsorized average erosivities and ~~finally~~ 17 yr wisorized and ~~for~~ kriged ~~values~~erosivities for the test region and for~~of~~ the entire area of Germany. Smoothing should reduce the influence of individual violent thunderstorm cells and reveal the regional pattern. In geostatistical analysis this decreases the sill of the semivariogram while the range increases as it changes from being dominated by thunderstorm cells to being dominated by the regional pattern. The regional trend was calculated as the difference between the square roots of semivariance at distances of 40 and 20 km divided by the difference in distance of 20 km to examine whether it was influenced by the individual smoothing steps. The effect of violent rain cells was calculated as the square root of the semivariance at a distance of 20 km divided by the difference in distance of 20 km minus the regional trend.

2.~~3~~4 ~~Return~~ Annual erosivity return periods

Rain erosivity usually follows long-tailed distributions.~~, which~~ This leads to the question of how frequent years of extraordinarily large erosivity are.~~, which requires~~ To answer this question, the development of cumulative distribution curves (for basic concepts see Stedinger et al., 1993) is required. Seventeen years are not sufficient to reliably estimate a cumulative distribution curve for every pixel. Therefore, ~~W~~we combined all annual erosivities of the total data set (452 503 pixels and 17 yr) after expressing each of them ~~the event erosivities of all individual years~~ relative to the corresponding winsorized and bias-corrected mean of ~~each~~ the pixel (in percent). This enabled the cumulative distribution curves to be calculated from a large data set (n = 7.7 million). ~~and t~~The expected maximum relative annual erosivity for a given return period ~~to~~ could then be estimated from the complementary cumulative distribution curve (exceedance). This was also done for the relative annual erosivities of the test region, calculated from 1 h rain data, to examine whether the general cumulative distribution curve also applies to smaller regions.

The erosivities, when calculated from 1 h rain data, are already smoothed and do not adequately reflect the extremes that result from data that are better ~~highly~~ resolved, such as the 5 min rain data. The cumulative distribution curve for the test region was also calculated using the 5 ~~-~~min rain data. Given that the cumulative distribution curves of the entire study area and the test region agree for the relative erosivities calculated from 1 h data, ~~this can also be~~we expected ~~to be the case for~~that the relative erosivities calculated from 5 min rain data of the test region can serve as a first estimate for the entire study region. The cumulative distribution curve for the test region calculated from 5 ~~-~~min data will then be a fair estimate of the return periods anywhere in the entire research area.

2.~~4~~5 ~~Annual cycle~~Seasonal distribution of ~~rain~~ erosivity

The seasonal ~~variation~~distribution of erosivity, calculated as the relative contribution of each day to total annual erosivity, is called erosion index distribution or EI distribution (Wischmeier and Smith, 1978). It is required in erosion modelling to determine the influence of seasonally varying soil cover due to crop development. The convolution of the seasonal effect of soil cover with the seasonal EI distribution results in the so-called crop and cover factor (C factor) of the USLE. The EI distribution was calculated for each pixel and averaged over all 452 503 pixels. Seventeen years of data still did not suffice to show similar amounts of erosivity on subsequent days, despite the large number of pixels. There was still considerable scatter that required smoothing to illustrate the seasonal distribution. Smoothing between individual days during the year involved three steps (for details of the methods see Tukey, 1977): first a 13-d centered median was calculated for each day. A centered median smooths but preserves the common trend signal ~~and the level shifts in the smooth~~ (Gallagher and Wise, 1981), which is also true for the two subsequent steps. A 3-d skip mean (leaving out the second day) was calculated from the results, followed by a 25-d centered ~~h~~Hanning mean (weighted mean with linearly decreasing weights). To account for the periodic nature of the EI distribution and to allow the smoothing methods to be applied at the start and the end of the year, t~~T~~he year was ~~recycled~~replicated and shifted by plus minus one year~~ to allow the smoothing methods to be applied at the boundaries~~.

~~The EI distribution deviated from the EI distribution used previously. This was especially pronounced during the winter months. However, r~~Radar measurements tend to have larger errors during wintertime with snowfall. The reduced reflectivity of snow particles may lead to an underestimation of the precipitation rate, while the increased reflectivity of melting particles in the bright band may cause an overestimation. Moreover, the lower boundary layer promotes a potential overshooting of the radar beam with regard to the precipitating cloud (Holleman et al., 2008; Wagner et al., 2012). ~~The~~Such measurement problems, if relevant, should especially influence EI distribution ~~deviated from the EI distribution used previously. This was especially pronounced~~ during ~~the~~ winter months and cause a deviation from measurements at meteorological stations. Therefore, we also calculated the EI distribution using data from 115 rain gauges distributed throughout Germany and covering 2001 to 2016. These data were taken from Fischer et al. (2018b). This data set will also be used in the discussion for comparison of recent radar-derived erosivities with recent raingauge-derived erosivities and with historic raingauge-derived erosivities taken from literature.

3 Results

3.~~2~~1 The effects of smoothing

The effects of smoothing on the appearance of the maps were negligible (compare Fig. 2 with Fig. A3 and A4 in the Appendix) because smoothing had only removed the extraordinarily large variability that exists on small temporal and spatial scales. However, the high data density revealed that even long-term averages were insufficient to remove all influence of erratic cells of violent rain and further attenuating steps had to follow. ~~Winsorizing reduced the standard deviation (SD) of a pixel over time from, on average, 49 N h^{-1} yr^{-1} to 39 N h^{-1} yr^{-1}, while bias correction left the mean for~~ of erosivity over ~~all pixels unchanged at 98 N h^{-1} yr^{-1}. Using kriging, the mean remained the same at 98 N h^{-1} yr^{-1}, because kriging is an unbiased linear interpolator that smoothed locally (over distances of about 10 to 15 km). Only the very extreme values~~, so ~~disappeared. Values lower than 45 N h^{-1} yr^{-1}, which had contributed 0.06% to the winsorized data, disappeared. In addition,~~

~~values larger than 450 N h^{-1} yr^{-1}, which had contributed 0.03% to the winsorized data, also disappeared.~~ erosivities smaller ~~than 45 N h^{-1} yr^{-1} higher than 455 N h^{-1} yr^{-1}, contribut 0.06% and 0.03% to the winsorized data respectively.~~

Annual sums of ~~R~~rain erosivity from 5 min ~~resolution~~ data for the test region varied most due ~~showed large small-scale variability caused by~~ the dominance of individual cells of violent rain~~, even for annual sums of erosivity~~ that did not overlap or fill the entire area (semivariogam I in Fig. 3a~~, upper panel~~). This was indicated by the short range (20 km) and high semivariance for that range (2749 N^2 h^{-2} yr^{-2}) (Table 1). ~~The range was only 20 km, indicating that the annual pattern was dominated by individual cells of violent rain. The semivariance for a lag of 20 km was 2749 N^2 h^{-2} yr^{-2} (Table 1). Using the normal distribution, in 31.8% of all cases the difference between~~The standard deviation of two pixels separated by 20 km ~~must~~ thus was~~then~~ ~~be larger than~~ 52 N h^{-1} yr^{-1} (square root of 2749 N^2 h^{-2} yr^{-2}), which is more than half of the average annual erosivity in Germany. After averaging both years (2011 and 2012), the semivariance for a ~~lag~~ distance of 20 km was only reduced to 1569 N^2 h^{-2} yr^{-2} and the range stayed the same at approximately 20 km (semivariogam III in Fig. 3a). Both findings indicated that even after averaging two years, the individual cells of violent rain were still fully detectable and had not merged to form a larger pattern. In consequence, the regional trend, albeit detectable, appeared minor (Table 1).

The effect when using data with a resolution of 1 h was almost as strong as when two years were averaged. Semivariance at a ~~lag~~ distance of 20 km was only 1667 N^2 h^{-2} yr^{-2} for annual values (semivariogam II in Fig. 3a) and 953 N^2 h^{-2} yr^{-2} for ~~biannual~~ biennial averages (semivariogam IV in Fig. 3a). Even more important~~ly~~, the regional trend became better visible~~,~~ due to smoothing of the extreme events by using 1 h instead of 5 min data.~~, the regional trend became better visible.~~ This regional trend is evident from the gradual increase in semivariance over the entire ~~range of lags~~distance of 50 km shown in Fig. 3. ~~This regional trend was already detectable in the annual erosivities calculated from 5-min data (Table 1), but did not appear to be significant due to the large semivariance caused by cells of violent rain.~~ Importantly, smoothing by using 1 h data did not change ~~overall~~ average erosivity. The ~~biannual~~ biennial average for the test region was 115 N h^{-1} yr^{-1} when calculated from 5 min data and 114 N h^{-1} yr^{-1} when calculated from 1 h data.

Averaging annual erosivities of the test region over 17 yr further reduced variability (semivariogram V in Fig 3a~~, upper panel~~). Semivariance strongly decreased to 197 N^2 h^{-2} yr^{-2} and the influence of individual cells of violent rain became small relative to the regional trend.~~,~~ This led ~~leading~~ to an almost linear increase in semivariance over distance. The influence of ~~extraordinary~~ extreme years in individual pixels was further reduced by winsorizing, which slightly reduced semivariance at 20 km distance to 190 N^2 h^{-2} yr^{-2} (semivariogram VIII in Fig 3b). For entire Germany, winsorizing reduced the standard deviation (SD) of a pixel over time from, on average, 49 N h^{-1} yr^{-1} to 39 N h^{-1} yr^{-1}, while bias correction left the mean of erosivity over all pixels unchanged at 96 N h^{-1} yr^{-1}. The effect on the appearance of the map was small (compare Fig. A3 and A4 in the Appendix) because only small erratic patches of extraordinarily high or low erosivity disappeared.

Finally, kriging reduced semivariance at 20 km distance to 121 N^2 h^{-2} yr^{-2}, leaving mainly the regional trend (semivariogram VI in Fig. 3a). Thus, the step from 5 ~~-~~min to 1 ~~-~~h resolution reduced semivariance at 20 km distance by a factor of 1.6 while~~;~~ averaging 17 yr reduced semivariance by a factor of 8.5~~;~~. ~~w~~Winsorizing contributed a factor of 1.04 and kriging a factor of 1.6. In total, semivariance was reduced by a factor of 23, indicating a pronounced patchiness of erosive rains on the annual scale that could not be leveled out by averaging 17 years alone. The effect of each smoothing step decreased with increasing distance. For a distance of 10 km, the combined factor was 32 while it was only 13 for a distance of 30 km. This was due to the decreasing importance of thunderstorm cells relative to the regional trend. ~~These factors became larger at shorter distances (e.g. the combined factor was 32 for a lag of 10 km) because the importance of thunderstorm cells, relative to the regional trend, increased. Correspondingly, the combined effect decreased with increasing distance (e.g., the factor was only 13 for a lag of 40 km) because the regional trend, which was not removed by the smoothing procedures, became increasingly important.~~ Independent of the degree of smoothing, ~~T~~the regional trend, extracted from the change in semivariance between ~~lags~~ distances of 20 km and 40 km, remained practically unchanged at 0.2 N h^{-1} yr^{-1} km^{-1}~~, independent of the degree of smoothing~~ (Table 1). In contrast, the effect of violent rain cells decreased greatly by the smoothing steps from 2.4 N h^{-1} yr^{-1} km^{-1} to 0.3 N h^{-1} yr^{-1} km^{-1}. The effect on the appearance of the map was again small (compare A4 in the Appendix and Fig. 2) because only large contrasts between close neighbors disappeared that are hardly visible due to the small pixel size. The main visible effect was the filling of the few gaps.

After winsorizing and kriging, the semivariances for the test region followed a linear regression through the origin almost perfectly ($r^2 = 0.9889$, n = 50; line through semivariogram VI in Fig. 3a). This indicated that the variation in erosivity over a distance of 50 km followed linear trends without any noise (nugget) or ~~small~~short-range structures that could be attributed to individual cells of violent rain. The semivariances, when calculated for the whole of Germany, were considerably ~~higher~~larger (twice as ~~high~~ large at a ~~lag~~ distance of 50 km; Fig. 3b, semivariogam VII~~, lower panel~~) and close to a linear trend only for short distances (e.g. a linear regression through the origin for the first 15 km yielded $r^2 = 0.9905$). For ~~larger~~ longer distances, the semivariogram followed an exponential model (nugget 4 N^2 h^{-2} yr^{-2}, partial sill 970 N^2 h^{-2} yr^{-2}, effective range 123 km). The larger semivariance and the exponential model were both caused by ~~T~~the inclusion of mountain areas with ~~high~~large erosivities and steep erosivity gradients that were missing in the test region~~, led to both the higherlarger semivariance and the exponential model~~.

3.~~1~~2 ~~Erosivity~~ R-factor map

Erosivity was on average 96 N h^{-1} yr^{-1} but varied between 46 N h^{-1} yr^{-1} and 454 N h^{-1} yr^{-1}. The regional pattern of erosivity (Fig. 2) was mainly determined by orography (for a detailed topographic map see Fig. A1 in the Appendix). ~~Highest~~ Largest values (above 185 N h^{-1} yr^{-1}) were found in the very south where the northern chain of the Alps reaches altitudes of almost 3000 m above sea level (a.s.l.). ~~Smaller~~ Lower mountain ranges are also characterized by ~~high~~larger mean annual erosivities than in their surrounding area (compare Fig. 1 or Fig. A1 in the Appendix with Fig. 2). For instance, the Bavarian Forest~~, in the southeast on the Czech border~~ with elevations of up to 1450 m a.s.l.~~,~~ exhibited annual erosivities of above 155 N h^{-1} yr^{-1}. The Ore Mountains ~~in the east also on the Czech border,~~ with elevations of up to 1244 m a.s.l., had erosivities mostly between 125 and 155 N h^{-1} yr^{-1}. Also mountain ranges like the Black Forest ~~(a mountain range in southwestern Germany oriented north-south)~~ or the Harz Mountains ~~(an area of highlarge erosivities located almost in the middle of northern Germany)~~ clearly shape the erosivity map. ~~Upwind~~Additionally, upwind-downwind effects were detectable. For example, the areas west-north-west (upwind) of the Harz Mountains had erosivities of between 70 and 80 N h^{-1} yr^{-1}, while the areas east-south-east (downwind) received less than 65 N h^{-1} yr^{-1}.

3.3 Annual erosivity ~~R~~return periods

The cumulative distribution of the relative annual erosivities followed a straight line in a probability plot fairly well when the logarithm was used (Fig. 4). This~~,~~ indicated~~ing~~ a log-normal distribution (log mean 1.96; log SD 0.19). A very similar cumulative distribution was found for annual ~~values~~ erosivities derived from the 1 ~~-~~h data of the test region (log mean 1.97; log SD 0.18)~~, while the~~. The distribution based on the less-smoothed 5 min data was considerably wider ~~for the less-smoothed 5-min data~~ (log mean 1.94; log SD 0.22). The annual expected erosivity was 88 %, 216 % and 273 % of the respective long-term mean for return periods of 2 yr, 30 yr, and 100 yr when the 5 min data were used (Fig. 4). It is important to note that these values apply for averages of 1 km² pixels and include the smoothing that results from the radar measurement, the radar reprocessing, and from using 5 min rain increments. Even more extreme~~r~~ years are expected to occur in reality.

3.4 ~~Erosion index distribution~~Seasonal distribution of erosivity

There was a pronounced peak in the ~~relative seasonal variation~~seasonal distribution of relative erosivity during summer months (Fig. 5). The ~~relative~~ daily erosion index increased rapidly from mid-April to mid-May ~~to a mean of~~and was 0.61 % d^{-1} on average in June, July and August.~~,~~ ~~and declined rapidly again f~~From mid-August to September the daily erosion index declined rapidly. ~~The contribution of~~In winter months the daily erosion index was small (mean of December, January, February, and March: 0.08 % d^{-1}). There was no detectable difference in the seasonal variation between different regions in Germany (see Fig. A5 in the Appendix). The cumulative distribution functions of different regions correlated with at least $r^2 = 0.998$ ($n = 365$).

Even more striking was the fact that this pattern required considerable smoothing to yield a continuous seasonal time course. The difference between subsequent days in the unsmoothed data was enormous (e.g., 1.5 % d^{-1}, 0.4 % d^{-1} and 0.4 % d^{-1} on July 29, 30 and 31). This was despite the large number of measurements (17 yr and 455 309 pixels) that were averaged for each day. It highlights ~~how extreme~~the exceptional strength of some violent rains~~ must be~~. Despite the rather small extent of individual erosivity cells, many of them occurred at the same day making a ~~high~~large relative contribution to total erosivity for this day. While particular days of the year are influenced by heavy precipitation, during other days no erosive rain fell anywhere within the research area. Seventeen years were not sufficient to level out the contrast between subsequent days. The results of the smoothing procedure show that even 221 yr (17 yr multiplied by a moving-average window of 13 d) ~~would~~ were not ~~be~~ sufficient to level out these differences.~~, because~~ ~~t~~Two additional smoothing steps had to be applied to arrive at a smooth time course. Despite the strong smoothing that was necessary for the probability density function, the smoothing did not change the cumulative distribution function (which is used for calculating C factors). The cumulative distribution functions of the original data and of the smoothed data correlated with $r^2=0.9998$ (n=365; both functions are shown in Fig. A5 in the Appendix).

The ~~EI~~ distribution of the daily erosion index~~, when~~ calculated from rain gauge data (1840 station years)~~,~~ was very similar to the distribution calculated from the much larger radar data set (compare solid and dashed lines in Fig. 5). This was especially true during winter months, when values derived from both measurement methods were considerably ~~higher~~larger than expected from previous analysis in the 1980s.

4 Discussion

4.1 Increase in erosivity

The most striking difference between the ~~German R map presently in use (~~Sauerborn map~~, 1994)~~ based on data from the 1960s to 1980s and the radar-derived map is a pronounced increase in erosivity. A German average of 58 N h^{-1} yr^{-1} was derived from the Sauerborn map (Auerswald et al., 2009), while the radar-derived map suggests an average of 96 N h^{-1} yr^{-1}. This increase will come along with an equal increase of predicted soil losses by 69 %. An almost identical increase resulted when the erosivity of meteorological stations, as reported by Sauerborn (1994), was compared with the erosivity derived from radar data at the same locations~~,~~. This ~~which~~ resulted in an increase of 63 % (open symbols in Fig. 6). Thus, the increase in erosivity is not an effect of the regression approach that was previously used or due to better capturing of extreme events by the contiguous radar data.

Fischer et al. (2018b) calculated erosivity for 33 of the Sauerborn stations from recent (2001 to 2016) rain gauge data. A comparison of these data with the Sauerborn data (1994) also showed a similar increase of 52 % (closed symbols in Fig. ~~5~~6). The increase in erosivity between the Sauerborn map and the new radar-derived map is thus also not an artefact of using radar data but the result of a true change in erosivity over time. This is further corroborated by Fiener et al. (2013), who analyzed long-term records from ten meteorological stations in western Germany. They found an increase in erosivity of 63 % between 1973 and 2007. Both independent findings leave little doubt that the pronouncedly higher values in the new erosivity map are a result of a change in weather properties and not a result of the difference in the applied methodologies, although we did expect the mean to increase due to the contiguous data set, which is better at recording rare extremes.

A time series of 17 yr is regarded to be too short in meteorology for calculating temporal trends. The data in Sauerborn (1994) were derived from different periods for different states. If we calculate the state-wide mean R factors from her transfer functions relative to the state-wide mean R factors of the radar-derived map and plot this relative R factor against the mean year from which the state-specific data originated, a 23-yr long period can be covered by the means (Fig. 7; years < 1990; the total time period of individual years covers an even wider range, mostly about ± 5 yr around the mean year). During this period there was a slight but insignificant increase in erosivity with time. This increase smoothly leads over to the steeper increase in radar-derived Germany-wide annual R factors if we express them again relative to the 17 yr mean (Fig. 7; years > 2000). Both data sets combined cover more than 60 years and yield a very highly significant regression (r^2 =

0.6388, n = 28) that indicates an accelerating increase in erosivity likely due to climate change. Furthermore, Fig. 7 indicates that at the end of the radar time series (2017) the R factor likely is already 20 % higher than the values depicted in Fig. 2.

4.2 Change in the regional pattern of erosivity

The regional patterns of the Sauerborn ~~erosivity~~ map ~~(1994) that is currently used,~~ and ~~that~~ of the radar-derived map, generally agree well, but with two exceptions. First, the radar-derived map shows distinctly ~~higher~~larger values south-east of the German Bight of the North Sea where the air masses coming from the North Sea are channeled by the Elbe river estuary and its Pleistocene meltwater valley and then hit the higher areas of the North German moraines. A ~~high~~large frequency of large rains is not unlikely in this situation. The reason that this was missed by Sauerborn (1994) using the data obtained by Hirche (1990) for Lower Saxony ~~is~~ might be mainly due to the ~~low~~small data density and the regression ~~approach~~with long-term rainfall. Only 18 stations were available for the whole of Lower Saxony and only five of them were in the area of ~~high~~large erosivity. Using the 18 stations in the state of Lower Saxony only, and ignoring the difference between landscapes, resulted in a rather poor regression with long-term annual rainfall (r^2 was only 0.32 for n=18), and therefore a large prediction error and considerable smoothing of the true erosivity pattern can be expected. For comparison: in Bavaria the regression with long-term rainfall yielded r^2 of 0.92 (for n=18; Rogler and Schwertmann, 1981).

The second difference in the pattern is that the radar-derived map reveals more detail than the regression-based map by Sauerborn (1994). This is especially evident in southern Germany where southwest-northeast oriented structures seem to follow ~~thunderstorm trains~~ tracks of thunderstorm movement. In the north-east quarter of Germany, where the pattern is not shaped by mountain ranges, a rather patchy pattern resulted. Although Sauerborn (1994) had already found a patchy pattern in this area it appears to be patchier now. ~~It is, a~~At present, it is difficult to decide whether this pattern is random due to large multi-cell clusters of rainstorms ~~and~~ that will level out on the long term, or whether landscape properties, e.g. the existence of large forests, cause a stable pattern in an area where other factors affecting the pattern are missing. More detailed variation may also be expected in mountainous areas but radar measurements cannot adequately show this variation. In the future, using data obtained by commercial microwave links as an additional source for retrieving precipitation (Chwala et al., 2012, 2016; Overeem et al., 2013) may improve high~~-~~-resolution estimates, particularly in these areas.

4.3 Change in the seasonal distribution of ~~the erosion index~~erosivity

The third pronounced difference between past and recent erosivities was found for the erosion index distribution. This distribution is needed for C -factor calculations (Wischmeier and Smith, 1978). A change in the seasonality of erosivity was already suggested by Fiener et al. (2013) analyzing an 80-yr time series. However, Fiener et al. (2013) used data from April to October only, and their results therefore cannot be compared directly with our results that show the most pronounced changes for the period from December to March.

At present, the C factors for entire Germany (DIN, 2017) are based on the erosion index distribution developed for Bavaria only ~~the erosion index developed~~ by Rogler and Schwertmann (1981) ~~for Bavaria is used for C-factor calculations in~~

~~Germany (e.g. Schwertmann et al., 1990; DIN, 2017)~~, although unpublished erosion indices are also available for other federal states (e.g., Hirche, 1990). The index distribution by Rogler and Schwertmann (1981) is characterized by very low values during winter months, which in turn causes a sharp increase during summer months. In contrast, the radar-based index, although still having a pronounced summer maximum, predicts a higher percentage of erosivity during winter. Rogler and Schwertmann (1981) found that only 1.5 % of the annual erosivity fell from January to March, while Fig. 5 indicates that these months contributed 6.9 % to annual erosivity. This deviation may be caused by a regional variation in the erosion index because the unpublished indices for other federal states also suggested a ~~higher~~larger contribution by winter months (e.g., January to March contributed 7.5 % in Lower Saxony according to Hirche, 1990). However, restricting our data set to Bavaria led to a very similar index during winter months (e.g., 6.2 % for January to March) to the index for the whole of Germany and the discrepancy with Rogler and Schwertmann (1981) remained. Furthermore we could not find significant differences when calculating the index distribution separately for different regions (Fig. 5A in the Appendix).

A second explanation might be~~is~~ that the Rogler and Schwertmann data (1981) were too limited to capture enough erosive rains during periods of infrequent erosive events. This explanation is corroborated by the large scatter between individual days that still exists in our data set (Fig. 5), although our data set was more than 50 000 times larger than the data set used by Rogler and Schwertmann (1981).

A third explanation could again be climate change. In Germany extreme rainfall events have increased in winter by 463 % during the last century with the trend greatest during the last few decades, while summer and autumn remained unchanged (Schönwiese et al., 2003).

The change in erosion index distribution may be regarded as being rather unimportant at first glance because erosivity is still dominated by precipitation in summer. This small increase in erosivity during the winter months, however, could have important consequences for the C factor of crops that~~, due to their crop development stage,~~ provide only ~~a small amount of soil cover~~small soil coverage~~ by the crop~~ during the winter. As there is practically no growth during winter, these crops are susceptible to erosion over a long period. ~~and t~~Thus they experience a considerable amount of erosivity, even though erosivity per day is ~~low~~small. ~~Calculating the C factor for continuous winter wheat from the soil loss ratios and cropping-stage dates reported by Schwertmann et al. (1990) yields a C factor of 0.04 if the erosion index from Rogler and Schwertmann (1980) is used. The C factor increases to 0.10 when the erosion index in Fig. 5 is applied. Thus, the predicted soil loss for continuous wheat is more than twice as high as previously expected due to the change in the erosion index (and four times higherlarger if the change in erosivity is also considered). While the C factor of the maize year in a typical maize-winter wheat rotation is currently regarded to be eight times higherlarger than that of winter wheat, it is only four times higherlarger when the new erosion index is applied. Furthermore, the C factor of the entire rotation increases by 15%.~~ For example, the C factor for continuous winter wheat increases from 0.04 to 0.10 when using the soil loss ratios taken from Auerswald et al. (1986) that entered DIN (2017) and the new erosion indices instead of those from Rogler and Schwertmann (1981).

4.4 Stochasticity

Soil erosion is characterized by a large temporal variability at a small spatial scale due to the stochastic character of erosive rains. About 20 yr are necessary, according to Wischmeier and Smith (1978), until this variability levels out and average soil loss approaches values predicted with the (R)USLE. Our data set covered 17 yr but significant additional smoothing was still necessary. One of the smoothing steps was to use hourly data, although 5 -min data would have been available. In one or two decades the data series may be long enough to remove some of the smoothing steps. In particular, it would be desirable to use data of 30 -min or even 5 -min resolution.

This pronounced stochasticity is due to the small size of convective rain cells. Just recently it has been shown by analyzing radar-derived rain pattern of the largest rainfall events that on average the rain amount is halved within a distance of only 2 km around the central point of a rain cell (Lochbihler et al., 2017). Given that rain amount is squared in the calculation of rain erosivity, the R factor decreases to one fourth within this distance. Larger areas are only covered if there is movement of the rain cells. This small size of rain cells questions the use of sparsely distributed rain gauges to derive rain erosivity. The inconsistent transfer functions among German states to derive erosivity from rainfall maps likely originated in the high stochasticity of rain gauge measurements under such conditions. It was only the unintended but unavoidable smoothing that was inherent in previous approaches that allowed deriving such maps. Radar technology enables us to replace this unintended smoothing by clearly defined statistical protocols and to quantify the effect of smoothing.

Another implication of this large variability is~~This implies~~ that 20 yr will still not be sufficient to level out extraordinary events. Most studies measuring soil erosion under natural rain use much shorter intervals that usually cover only a few years and rarely exceed ten years (see Auerswald et al., 2009, for a meta-analysis of German studies and Cerdan et al., 2010, for European studies). The interpretation of such short-term studies and the applicability of the results are limited due to the pronounced variability of natural rains.

~~We applied stepwise smoothing in order to minimize the disadvantages inherent in different smoothing procedures and to be able to smooth in time and space. We used rain data with hourly resolution instead of more highly resolved data and compensated for the disadvantages by using a scaling factor and by adjusting the threshold intensity according to Fischer et al. (2018). This procedure smoothed between individual rains. We added winsorizing and bias correction to smooth between years at a certain location. Finally, we added geostatistical smoothing to level out differences between neighboring locations caused by the small spatial extent of erosive rain cells. While the effects of winsorizing and geostatistical smoothing are rather easy to assess, the effects are less clear when hourly resolved data are used, although the mean erosivity was identical for our test region when calculated with both resolutions. The pronounced influence of orography on the R-factor map could have, at least partly, been caused by this smoothing step. Orographic rainfall may increase hourly rainfall but it may not, to the same degree, increase high intensity peaks that exert a dominant influence on erosivity. Still, this is presently speculative because the high variability of erosive events means that this question cannot be answered using a 17-yr time series. In one or two decades the data series may be long enough to use data of 30-min or even 5-min resolution.~~

In addition, the erosion index distribution required ~~pronounced~~ considerable smoothing to improve representation of the seasonal variation. Without smoothing, t~~T~~he shift of a certain crop stage by only one day can cause large discrepancies in the resulting C factor, depending on whether a day of large erosivity in the past is included or excluded at the bounds of the crop stage period. Smoothing can prevent this. This is especially important for short crop stage~~s~~ periods, while the effect becomes small for longer periods. For instance, the monthly sums of the smoothed data correlated closely with the sums of the unsmoothed data (coefficient of determination: 0.995; Nash-Sutcliffe efficiency: 0.994).

5. Conclusions

Radar-derived rainfall data enable~~s~~ to derive highly resolved and contiguous maps of erosivity~~ to be derived. This yielded a rain erosivity map~~ with high spatial detail. This avoids~~and avoided~~ errors in landscapes with insufficient rain gauge density. The ~~data~~ analysis showed that present (2001 to 2017) rain erosivity is considerably higher than erosivity in the past (1960s to 1980s)~~what existing erosivity maps showed previously expected~~. Furthermore, the seasonal distribution of rain erosivity also deviate~~d~~s from that of the past period. ~~current expectations and indicated that w~~Winter months ~~make a higher~~ contribute~~ion~~ more to total erosivity than previously ~~thought~~recorded. Considerably more erosion can be expected for crops that are at a highly susceptible stage of development in winter. In consequence, the predicted soil loss will change pronouncedly by using ~~radar-derived~~recent erosivity and the ranking of crops regarding their erosion potential will change. This will have definite consequences for agricultural extension and advisory services, landscape planning and even political decisions.

Data availability

The R factors of the 11266 German communities can be obtained from https://doi.org/....

A shape file containing the entire map with a resolution of 1 km² can be obtained from https://doi.org/....

Unsmoothed maps of all individual years since 2001 will become available at www.dwd.de/... until the end of 2019. Earlier requests may be directed to Tanja.Winterrath@dwd.de.

Author contribution

KA designed the analysis, which was mainly carried out by FKF. TW provided most data and the knowledge about all steps involved in radar data creation. KA prepared the manuscript with contributions by FKF and TW.

Acknowledgements

This study was part of the project “Ermittlung des Raum- und Jahreszeitmusters der Regenerosivität in Bayern aus radargestützten Niederschlagsdaten zur Verbesserung der Erosionsprognose mit der Allgemeinen Bodenabtragsgleichung” at the Bavarian State Research Center for Agriculture (PI Robert Brandhuber). It was funded by the Bayerisches Staatsministerium für Ernährung, Landwirtschaft und Forsten (A/15/17). The RADKLIM data were provided by the project "Erstellung einer dekadischen radargestützten hochauflösenden Niederschlagsklimatologie für Deutschland zur Auswertung der rezenten Änderung des Extremverhaltens von Niederschlag (Kurztitel: Radarklimatologie)" financed by the Strategic Agencies' Alliance "Adaptation to Climate Change" consisting of the Federal Office of Civil Protection and Disaster Assistance (BBK), the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR), the Bundesanstalt Technisches Hilfswerk (THW), the Umweltbundesamt (UBA), and the Deutscher Wetterdienst (DWD). Melanie Treisch helped with ArcGIS operations, Karin Levin provided language editing, Anton Vrieling provided helpful comments during revision and Helmut Rogler has, for many years, requested that the German R-factor map may be updated.

References

Auerswald, K., Fiener, P., Dikau, R.: Rates of sheet and rill erosion in Germany – a meta-analysis~~.~~, Geomorph., 111, 182–193. http://dx.doi.org/10.1016/j.geomorph.2009.04.018, 2009.

Auerswald, K., Kainz, M., Vogl, W.: Vergleich der Erosionsgefährdung durch Maisfruchtfolgen (C-Faktor), Bayerisches Landwirtschaftliches Jahrbuch, 63, 3–8, 1986.

Bartels, H., Weigl, E., Reich, T., Lang, P., Wagner, A., Kohler, O., Gerlach, N.: Projekt RADOLAN: Routineverfahren zur Online-Aneichung der Radarniederschlagsdaten mit Hilfe von automatischen Bodenniederschlagsstationen (Ombrometer), Deutscher Wetterdienst, Hydrometeorologie, Offenbach/M., http://www.laenderfinanzierungsprogramm.de/cms/WaBoAb_prod/WaBoAb/Vorhaben/LAWA/Vorhaben_des_ehemaligen_Ausschusses_Daten/DK_5.68/RADOLAN_Abschlussbericht_2006.pdf (last access 12 Dec 2017), 2004.

Bringi, V.N, Chandrasekar, V.: Polarimetric Doppler Weather Radar: Principles and Applications, Cambridge Uni. Press, 2001.

Burt, T., Boardman, J., Foster, I., Howden, N.: More rain, less soil: Long-term changes in rainfall intensity with climate change~~.~~, Earth Surf. Process. Landf., 41, 563–~~-~~566, 2016.

Chow, V.T., 1953. Frequency Analysis of Hydrologic Data with Special Application to Rainfall Intensities, University of Illinois. Engineering Experiment Station. Bulletin 414. Online available at: www.ideals.illinois.edu/handle/2142/4107 (last access: 13 November 2018).

Chwala, C., Gmeiner, A., Qiu, W., Hipp, S., Nienaber, D., Siart, U., Eibert, T., Pohl, M., Seltmann, J., Fritz, J., Kunstmann, H.: Precipitation observation using micro-wave backhaul links in the alpine and pre-alpine region of southern Germany, Hydrol. Earth Syst. Sci., 16, 2647-2661, https://doi.org/10.5194/hess-16-2647-2012, 2012.

Chwala, C., Keis, F., Kunstmann, H.: Real-time data acquisition of commercial microwave link networks for hydrometeorological applications, Atmos. Meas. Tech., 9, 991-999, 2016.

DIN – Deutsches Institut für Normung: DIN 19708: 2005-02 Bodenbeschaffenheit – Ermittlung der Erosionsgefährdung von Böden durch Wasser mit Hilfe der ABAG, Beuth-Verlag, Berlin, 2017.

Dixon, W.J., Yuen, K.: Trimming and winsorization: A review, Statistical Papers, 15, 157-170, 1974.

Cerdan, O., Govers, G., Le Bissonnais, Y., Van Oost, K., Poesen, J., Saby, N., Gobin, A., Vacca, A., Quinton, J., Auerswald, K., Klik, A., Kwaad, F. J. P. M., Raclot, D., Ionita, I., Rejman, J., Rousseva, S., Muxart, T., Roxo, M. J., Dostal, T.: Rates and spatial variations of soil erosion in Europe: a study based on erosion plot data, Geomorph., 122, 167–177. doi:10.1016/j.geomorph.2010.06.011, 2010.

Emde, K.: Experimentelle Untersuchungen zu Oberflächenabfluß und Bodenaustrag in Verbindung mit Starkregen bei verschiedenen Bewirtschaftungssystemen in Weinbergsarealen des oberen Rheingaus, Geisenheimer Berichte 12. Gesellschaft zur Förderung der Forschungsanstalt Geisenheim, Geisenheim, 1992.

Fairman, J. G., Shultz, D. M., Kirshbaum, D. J., Hray, S. L., Barrett, A. I.: A radar-based rainfall climatology of Great Britain and Ireland, Weather 70, 153–158. DOI: 10.1002/wea.2486, 2015.

Fiener, P., Auerswald, K.: Spatial variability of rainfall on a sub-kilometre scale, Earth Surf. Process. Landf., 34, 848–859, 2009.

Fiener, P., Neuhaus, P., Botschek, J.: Long-term trends in rainfall erosivity – analysis of high resolution precipitation time series (1937–2007) from Western Germany, Agric. Forest Meteorol., 171–172, 115–123, 2013.

Fischer, F., Hauck, J., Brandhuber, R., Weigl, E., Maier, H., Auerswald, K.: Spatio-temporal variability of erosivity estimated from highly resolved and adjusted radar rain data, Agric. Forest Meteorol., 223, 72–80, doi: 10.1016/j.agrformet.2016.03.024, 2016.

Fischer, F. K., Kistler, M., Brandhuber, R., Maier, H., Treisch, M., Auerswald, K.: Validation of official erosion modelling based on high-resolution radar rain data by aerial photo erosion classification, Earth Surf. Process. Landf. 43, 187–194, doi: 10.1002/esp.4216, 2018a.

Fischer, F. K., Winterrath T., Auerswald K.: Temporal- and spatial-scale and positional effects on rain erosivity derived from point-scale and contiguous rain data, Hydrol. Earth Syst. Sci., https://doi.org/10.5194/hess-22-6505-2018, 2018b.

Gallagher, N. C., Wise, G. L.: A theoretical analysis of the properties of median filters, IEEE Transact. Acoustics, Speech, Signal Processing, 29, 1138–1141, 1981.

Gräler, B., Pebesma, E., Heuvelink, G.: Spatio-temporal interpolation using gstat. The R Journal, 8, 204-218, 2016.

Hardegree, S.P., Van Vactor, S.S., Levinson, D.H., Winstral, A.H.: Evaluation of NEXRAD radar precipitation products for natural resource applications, Rangel. Ecol. Manag., 61, 346–353, 2008.

Hirche, D.: Die Erosivität der Niederschläge in Niedersachsen~~.~~, Diploma Thesis, University Braunschweig. 155 p., 1990.

Holleman, I., Michelson, D., Galli, G., Germann, U., Peura, M.: Quality information for radars and radar data, OPERA, Network of European Meteorological Services, http://opera.radar.tugraz.at/docum/opera_2/OPERA_2005_19_DataQuality.pdf (last access: 15 December 2018), 2008.

Koistinen, J., Michelson, D.B.: BALTEX weather radar-based precipitation products and their accuracies, Boreal Env. Res., 7, 253–263, 2002.

Krajewski, W. F., Ciach, G. J., Habib, E.: An analysis of small-scale rainfall variability in different climatic regimes, Hydrol. Sci. J., 48, 151–162. http://dx.doi.org/10.1623/hysj.48.2.151.44694, 2003.

Lochbihler, K., Lenderink, G., Siebesma A. P.: The spatial extent of rainfall events and its relation to precipitation scaling, Geophys. Res. Lett., 44, 8629–8636, doi:10.1002/2017GL074857, 2017.

Meischner, P., Collier, C., Illingworth, A., Joss, J., Randeu, W.: Advanced weather radar systems in Europe: The COST 75 action, Bull. Amer. Meteorol. Soc., 78, 1411-1430, 1997.

Michelson, D., Szturc, J., Gill, R. S., Peura, M.: Community-based weather radar networking with BALTRAD, The sixth European Conference on Radar in Meteorology and Hydrology ERAD Proceedings, 6 p. http://www.erad2010.com/pdf/oral/wednesday/dataex/01_ERAD2010_0170.pdf (last access 14 May 2018), 2010.

Morgan, R. P. C., Quinton, J. N., Smith, R. E., Govers, G., Poesen, J. W. A., Auerswald, K., Chisci, G., Torri, D., Styczen, M.E.: Reply to discussion on 'The European soil erosion model (EUROSEM): A process-based approach for predicting soil loss from fields and small catchments', Earth Surf. Process., 24, 567-568, 1999.

Mutchler, C. K., Carter, C. E.: Soil erodibility variation during the year, Transact. Amer. Soc. Agric. Eng., 26, 1102-1104, 1983.

Nearing, M. A., Yin, S.-Q., Borrelli, P., Polyakov, V. O.: Rainfall erosivity: An historical review. Catena, 157, 357–362, 2017.

O'Haver, T.: A pragmatic introduction to signal processing, https://terpconnect.umd.edu/~toh/spectrum/IntroToSignalProcessing.pdf (last access: 15 December 2018), 2018.

Overeem, A., Leijnse, H., Uijlenhoet, R.: Country-wide rainfall maps from cellular communication networks, Proc. Nat. Acad. Sci., 110, 2741-2745, 2013.

Pedersen, L., Jensen, N.E., Christensen, L. E., Madsen, H.: Quantification of the spatial variability of rainfall based on a dense network of rain gauges, Atmospheric Res., 95, 441–454. DOI: 10.1016/j.atmosres.2009.11.007, 2010.

Peleg, N., Marra, F., Fatichi, S., Paschalis, A., Molnar, P.: Spatial variability of extreme rainfall at radar subpixel scale, J. Hydrol., 556, 922–933. doi: 10.1016/j.jhydrol.2016.05.033, 2016.

Puetter, R. C., Gosnell, T. R., Yahil, A.: Digital image reconstruction: Deblurring and denoising, Annual Rev. Astron. Astrophysics, 43, 139-194, 2005.

Quantitative Decisions: Smoothing, http://www.quantdec.com/Excel/smoothing.htm (last access: 15 December 2018), 2004.

R Core Team: R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/ (last access: 15 December 2018), 2018.

Renard, K. G., Foster, G. R., Weesies, G. A., Porter, J. P.: RUSLE - Revised universal soil loss equation, J. Soil Water Conserv. 46, 30–33, 1991.

Richter, G.: The soil erosion measurement station and its program~~.~~, Forschungsstelle Bodenerosion, 10, 97–108, 1991.

Rogler, H., Schwertmann, U.: Erosivität der Niederschläge und Isoerodentkarte Bayerns, Zeitschrift für Kulturtechnik und Flurbereinigung, 22, 99–112, 1981.

Sauerborn, P.: Die Erosivität der Niederschläge in Deutschland. Ein Beitrag zur quantitativen Prognose der Bodenerosion durch Wasser in Mitteleuropa, Bonner Bodenkundliche Abhandlungen, 13, 1994.

Schmidt, J.: The impact of rainfall on sediment transport by sheetflow, In: Bork, H.-R., De Ploey, J., Schick, A.P. (eds): Erosion, Transport and Deposition Processes – Theory and Models, Catena Suppl., 19, 9-17, 1991.

Schönwiese, C.-D., Grieser, J., Trömel, S.: Secular change of extreme monthly precipitation in Europe, Theoretical Applied Climatol., 75, 245-250, 2003.

~~Schwertmann, U., Vogl, W., Kainz, M.: Bodenerosion durch Wasser, Vorhersage des Abtrags und Bewertung von Gegenmaßnahmen. 2. Edition. Ulmer Verlag Stuttgart, 1990.~~

Simonoff, J.S.: Smoothing Methods in Statistics, Springer, 340 pp., 1996.

Stedinger, J. R., Vogel, R. M., Foufoula-Georgiou, E.: Frequency analysis of extreme events, D. R. Maidment~~,~~(ed.) ~~Editor-in-Chief~~~~Chapter 18,~~ Handbook of Hydrology, McGraw-Hill Book Company,~~ D. R. Maidment, Editor-in-Chief~~. Chapter 18, 66 p., https://engineering.tufts.edu/cee/people/vogel/documents/frequencyAnalysis.pdf (last access: 15 December 2018), 1993.

Tukey, J. W.: Exploratory Data Analysis. Reading, Mass.: Addison - Wesley, 712 pp., 1977.

UK Met Office: Fact Sheet No. 3: Water in the Atmosphere, Met Office, Exeter, UK. https://web.archive.org/web/20120114162401/http://www.metoffice.gov.uk/media/pdf/4/1/No._03_-_Water_in_the_Atmosphere.pdf (last access: 15 December 2018), 2007.

Vaezi, A. R., Zarrinabadi, E., Auerswald, K.: Interaction of land use, slope gradient and rain sequence on runoff and soil loss from weakly aggregated semi-arid soils, Soil & Tillage Research, 172, 22–31, 2017, http://dx.doi.org/10.1016/j.still.2017.05.001

van Dijk, A. I. J. M., Bruijnzeel, L. A., Rosewell, C. J.: Rainfall intensity-kinetic energy relationships: A critical literature appraisal, J. Hydrol., 261, 1-23, 2002.

Vrieling, A., Sterk, G., de Jong, S. M.: Satellite-based estimation of rainfall erosivity for Africa, J. Hydrol., 395, 235-241, 2010.

Vrieling, A., Hoedjes, J. C. B., van der Velde, M.: Towards large-scale monitoring of soil erosion in Africa: Accounting for the dynamics of rainfall erosivity, Global Planetary Change, 115, 33-43, 2014.

Wagner, A., Seltmann, J., and Kunstmann, H.: Joint statistical correction of clutters, spokes and beam height for a radar derived precipitation climatology in southern Germany, Hydrol. Earth Syst. Sci., 16, 4101–4117, doi:10.5194/hess-16-4101-2012, 2012.

Wedin, O., Bogren, J., Grabec, I.: Data filtering methods, https://cordis.europa.eu/docs/projects/cnect/5/215455/080/deliverables/ROADIDEA-D3-1-Data-filtering-methods-V1-1.pdf (last access: 15 December 2018), 2008.

Wilken, F., Baur, M., Sommer, M., Deumlich, D., Bens, O., Fiener, P.: Uncertainties in rainfall kinetic energy-intensity relations for soil erosion modeling, Catena, 171, 234-244, 2018.

Williams, J. R., Berndt, H. D.: Sediment yield prediction based on watershed hydrology, Trans. Amer. Soc. Agr. Eng., 20, 1100-1104, 1977.

Winterrath, T., Rosenow, W., Weigl, E.: On the DWD quantitative precipitation analysis and nowcasting system for real-time application in German flood risk management, Weather Radar and Hydrology, IAHS Publ. 351, 323-329, 2012.

Winterrath, T., Brendel, C., Hafer, M., Junghänel, T., Klameth, A., Walawender, E., Weigl, E., Becker, A.: Erstellung einer radargestützten Niederschlagsklimatologie, Berichte des Deutschen Wetterdienstes, 251, 73 p. , 2017.

Winterrath, T., Brendel, C., Hafer, M., Junghänel, T., Klameth, A., Lengfeld, K., Walawender, E., Weigl, E., Becker, A.: RADKLIM Version 2017.002: Reprocessed gauge-adjusted radar data, one-hour precipitation sums (RW), doi: 10.5676/DWD/RADKLIM_RW_V2017.002, 2018.

Wischmeier, W. H.: A rainfall erosion index for a universal soil-loss equation, Soil Sci. Soc. Am. Proc., 23, 246–249, 1959.

Wischmeier, W. H., Smith, D. D.: Rainfall energy and its relationship to soil loss, Transact. Am. Geophysical Union, 39, 285-291, 1958.

Wischmeier, W.H., Smith, D.D.: Predicting rainfall erosion losses, Agricultural Handbook, Issue 537. US Department of Agriculture: Washington, DC, 1978.

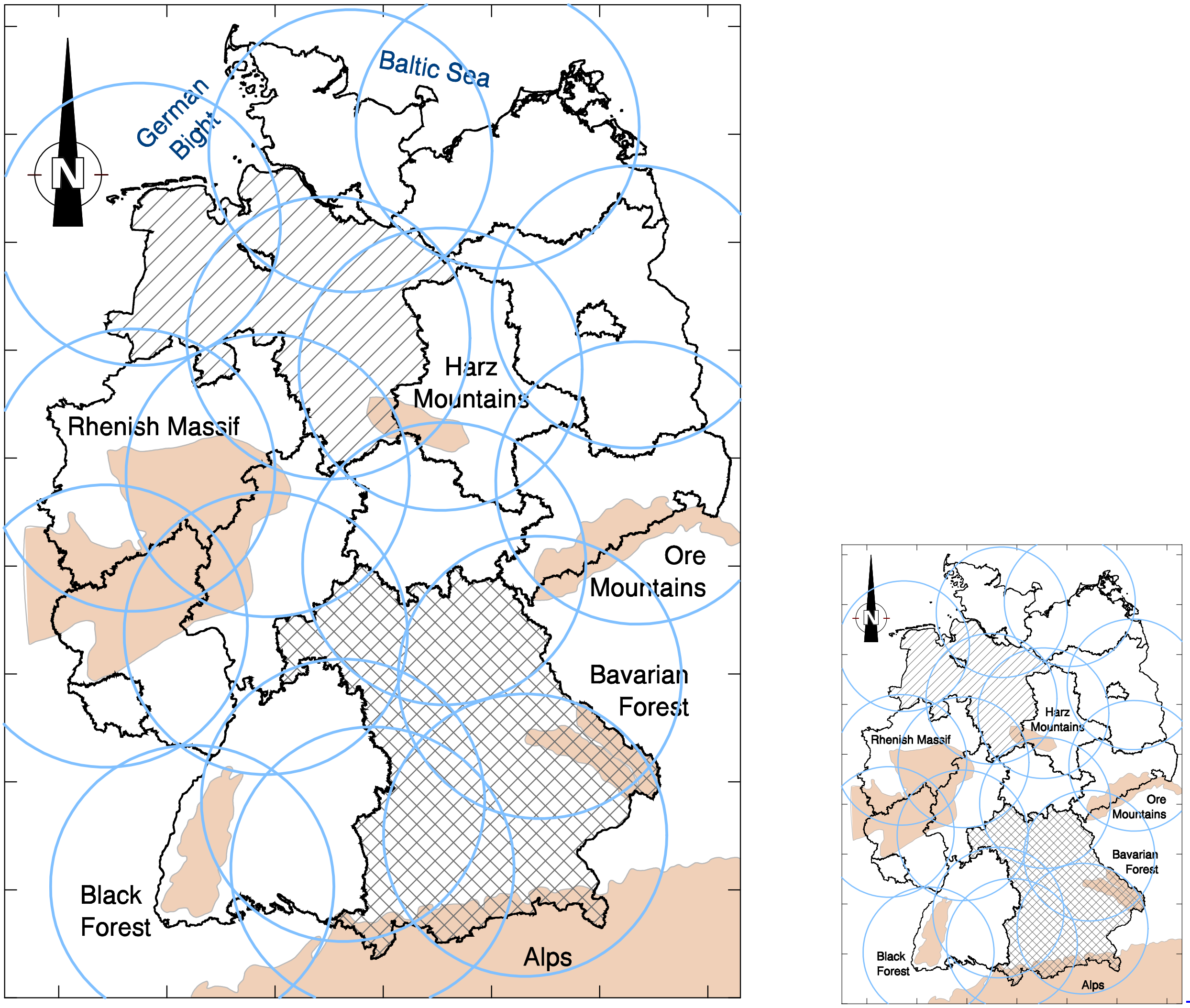


Figure 1: Coverage (blue circles) of the 17 German ~~rain~~ weather radars for a range (utilized radius) of 128 km and the tower locations in 2017 ~~configuration tower locations~~ (locations of some radar towers have changed over time). Black lines denote federal states; the federal states of Bavaria (cross-hatched), Lower Saxony (hatched) and selected mountain ranges (light brown) are mentioned in the text. Axis ticks represent distances of 100 km. A detailed topographic map can be found in Fig. A1 in the Appendix.

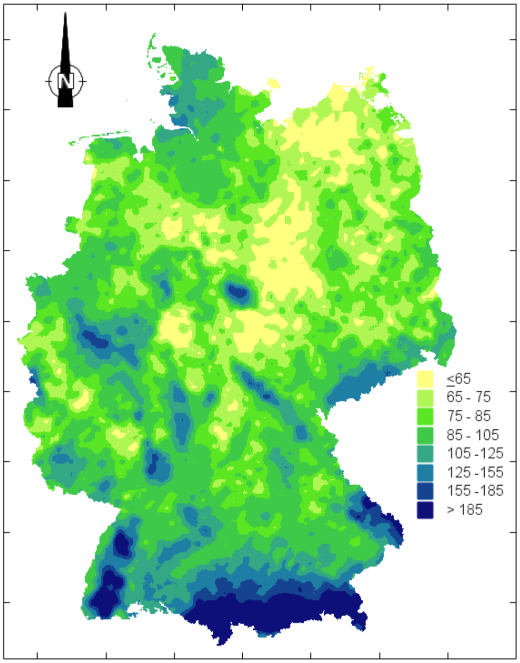
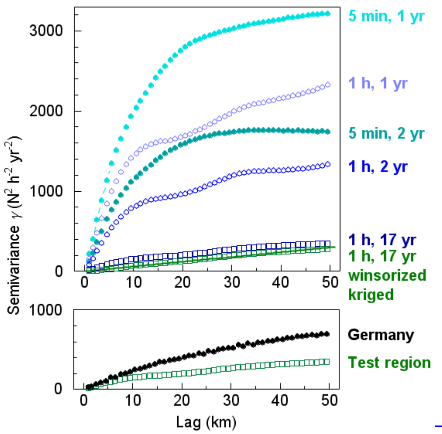


Figure 2: Annual average ~~Erosivity~~R factor (N h^{-1} yr^{-1}) map of Germany from 17 yr of radar rain data. Axes ticks represent distances of 100 km. Color classes from yellow to dark blue comprise approximately 10 %, 20 %, 20 %, 25 %, 15 %, 4 %, 3 %, and 3 % of the area, respectively. For a comparison with the Sauerborn (1994) map see Fig. A2 in the Appendix. For comparison with the map before winsorizing and before kriging see Figs. ~~A1~~ A3 and ~~A2~~A4 ~~in the Appendix~~. ~~For a~~Average ~~values~~ R factors for the 294 local authority areas (average ~~size~~ area 1214 km²)~~,~~ ~~see~~ are given in Table A1 in the Appendix. Average values for the 11 254 communities (average ~~size~~ area 32 km²) can be obtained at https://www.lfl.bayern.de/iab/index.php.



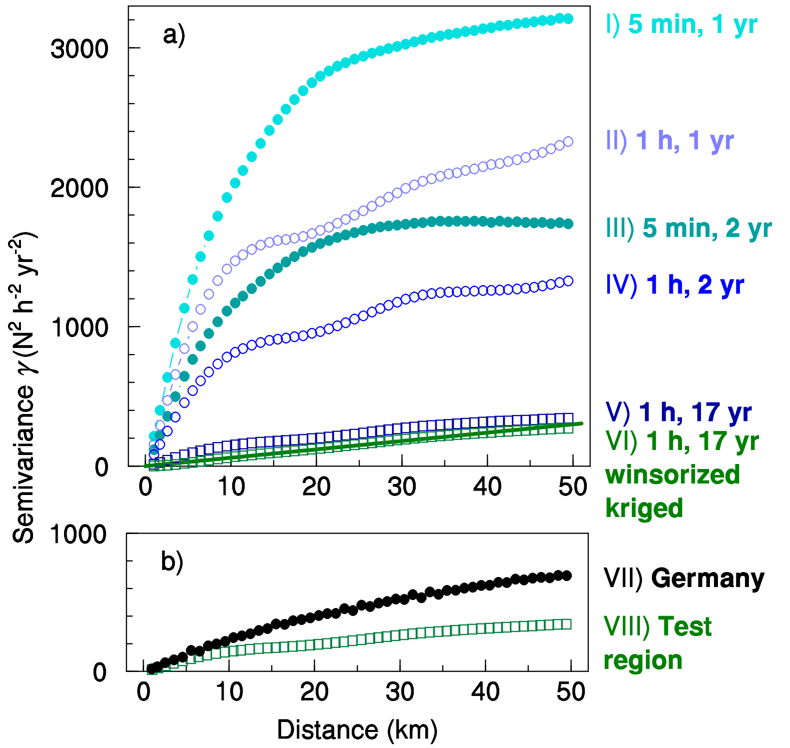


Figure 3: ~~Upper panel:~~a) Experimental s~~S~~emivariograms of annual erosivity of the test region for different temporal resolutions of rain data (5 min and 1 h), different averaging (1 yr [2011 + 2012], 2 yr [mean of 2011 + 2012], 17 yr [2001 to 2017]), winsorizing and kriging ~~for the test region~~ (for selected ~~lag~~ distance classes see Table 1). The line through ~~the~~ semivariogram VI~~ances of the 1 h, 17 yr, winsorized and kriged data~~ is a linear regression through the origin ($r^2 = 0.9889$).

b)

~~Lower panel:~~ Comparison of semivariances for the 1 h, 17 yr and winsorized data before kriging for the test region and for the whole of Germany.

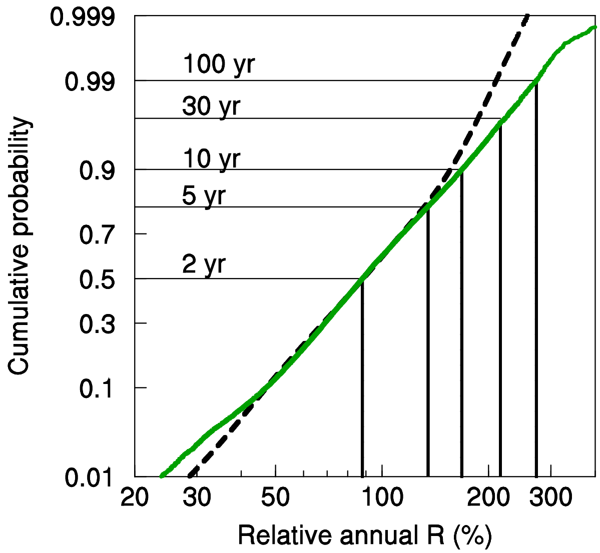


Figure 4: Cumulative distribution curve of the annual R factor relative to the long-term ~~annual~~ mean R factor of a pixel. Dashed black line applies for erosivities derived from 1 ~~-~~h data for the whole of Germany and 17 yr (n = 7.7 million). Solid green line applies for erosivities derived from 5 ~~-~~min data for the test region and 2 yr (n = 24 770). Straight vertical and horizontal lines indicate return periods between 2 yr and 100 yr. The y axis is probability scaled, the x axis is log scaled.

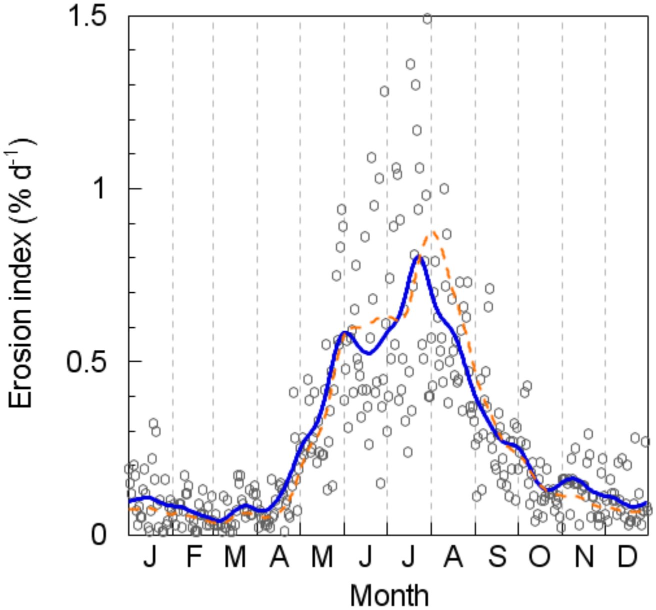


Figure 5: Measured (circles) and smoothed (solid blue line) daily erosion index from radar data. The daily erosion index calculated from measurements between 2001 and 2016 at 115 rain gauges distributed throughout Germany is given for comparison (orange dashed line). For C-factor calculations the smoothed values can be taken from Table A2 in the Appendix. Comparison of measured daily erosion indices separated for different regions in Germany and the respective cumulative distribution curves are depicted in Fig. A5 in the Appendix.

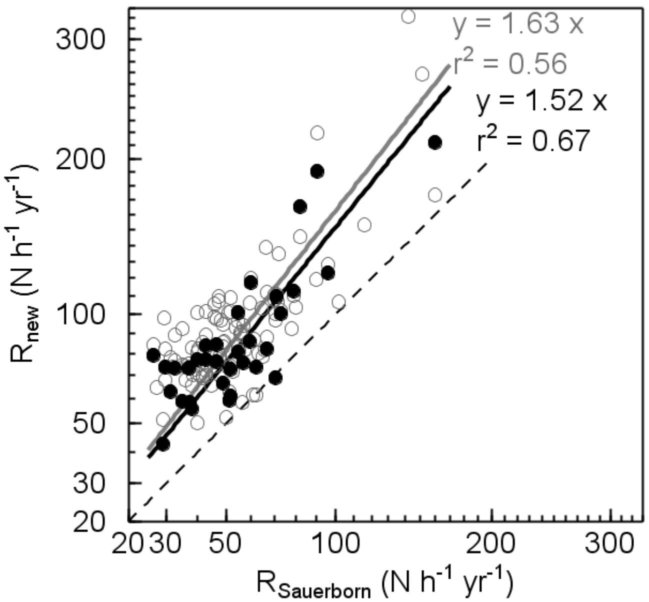


Figure 6: Comparison of past mean erosivities derived from rain gauge data of the 1960s to 1980s as reported by Sauerborn (1994)~~, measured mainly in the 1960s to 1980s,~~ with recent mean erosivities of the 2000s to 2010s. Recent erosivities were either determined from rain gauge ~~measurements~~ data at the same meteorological stations (mean of 2001 to 2016; taken from Fischer et al., 2018b; n = 33; filled circles) or from radar data (mean of 2001 to 2017 and all radar pixels at a distance of <1.5 km from the meteorological stations; n = 101, open circles). Both axes are square-root scaled to improve resolution at low erosivities. Dashed line denotes 1:1. Solid lines are regressions through the origin.

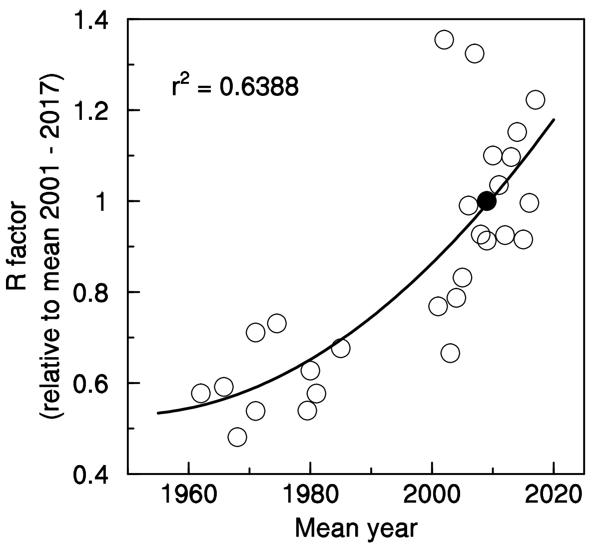


Fig. 7: Average R factor relative to the 17 yr mean radar-derived R factor depending on the mean year of data origin. Data below year 1990 are calculated from state-wide averages determined from meteorological station records; year is the mean year of station records. Data above year 2000 are radar-derived R factors of entire Germany for individual years. The closed circle denotes the reference point (present map).

Table 1: Influence of temporal resolution of rain data (5 min and 1 h), averaging (1 yr, 2 yr, and 17 yr), winsorizing and kriging on the semivariance (gamma) at three ~~lags~~ distances *h*. For complete semivariograms see Fig. 3~~a, upper panel~~.

Variable (Number in Fig. 3)	gamma at h = 10 km (N^2 h^{-2} yr^{-2})	gamma at h = 20 km (N^2 h^{-2} yr^{-2})	gamma at h = 40 km (N^2 h^{-2} yr^{-2})	Regional trend ① (N h^{-1} yr^{-1} km^{-1})	Effect of violent rain cells② (N h^{-1} yr^{-1} km^{-1})
5-min annual erosivity (I)	1925	2749	3136	0.2	2.4
5-min biennial erosivity (II)	1111	1569	1755	0.1	1.9
1-h annual erosivity (III)	1413	1667	2147	0.3	1.8
1-h biennial erosivity (IV)	782	953	1259	0.2	1.3
1-h 17-yr mean erosivity (V)	144	197	315	0.2	0.5
1-h winsorized 17-yr mean erosivity (VIII)	139	190	309	0.2	0.5
1-h kriged 17-yr erosivity (VI)	60	121	239	0.2	0.3

① The regional trend was calculated as the difference between the square roots of gamma at distances of 40 and 20 km divided by the difference in distance of 20 km.

② The effect of violent rain cells was calculated as the square root of gamma at a distance of 20 km divided by the difference in distance of 20 km minus the regional trend.

Appendix

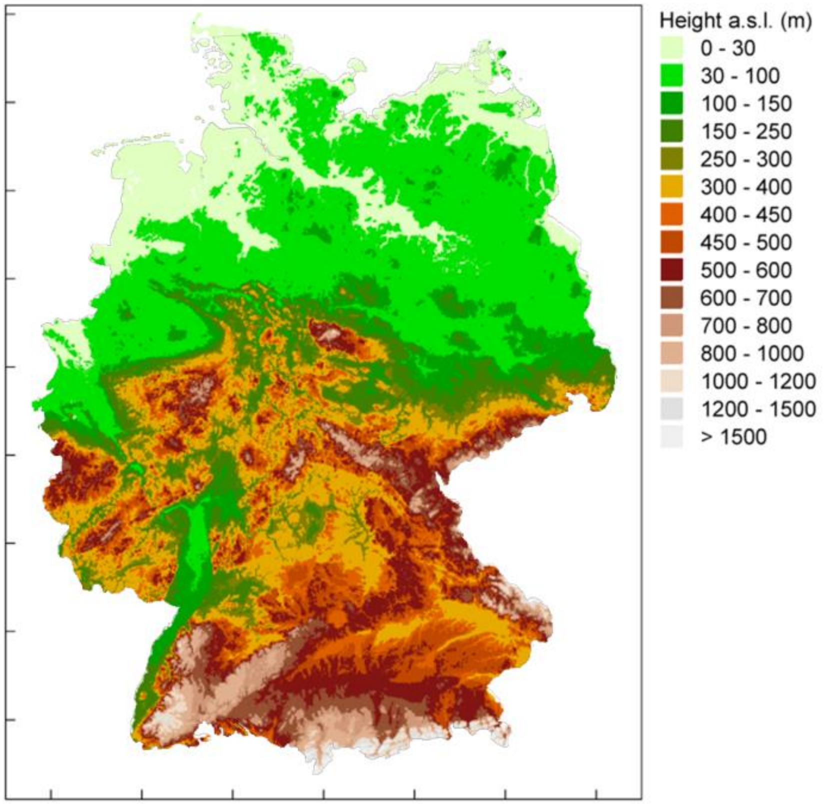


Figure A1: Topographic map of Germany. Axes ticks represent distances of 100 km. Data were taken from www.bkg.bund.de

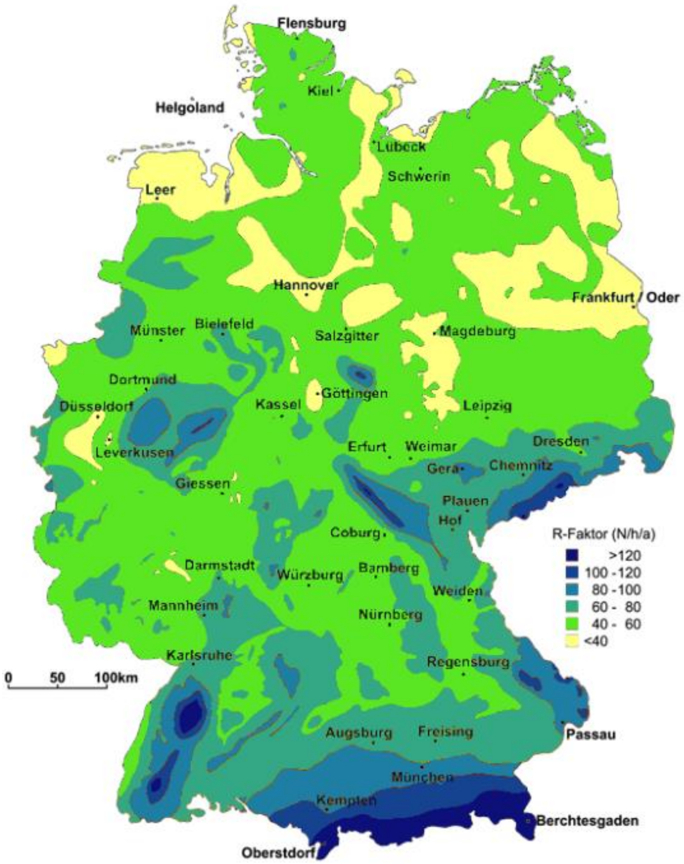


Figure A2: The Sauerborn (1994) R--factor map taken from Auerswald and von Perger (1998). For an easy comparison, colors were adjusted to match the present maps (i.e., an R factor class multiplied by 1.66 received the same color as in the present maps; the factor 1.66 accounts for the mean increase in R between the Sauerborn map and the present map).

Auerswald, K., v. Perger P.: Bodenerosion durch Wasser - Ursachen, Schutzmaßnahmen und Prognose mit PCABAG. AID-Heft 1378, Publisher AID, Bonn, 1998.

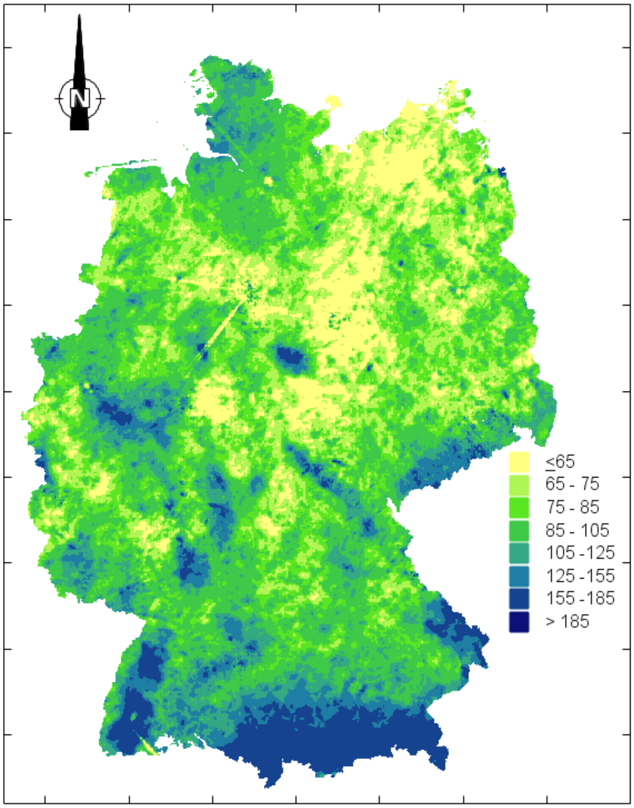


Figure ~~A1~~A3: ~~EAnnual erosivity~~ Annual average R–-factor map (N h^{-1} yr^{-1}) of Germany from 17 yr of radar rain data before statistical smoothing by winsorizing, removal of spokes and kriging. Axes ticks represent distances of 100 km.

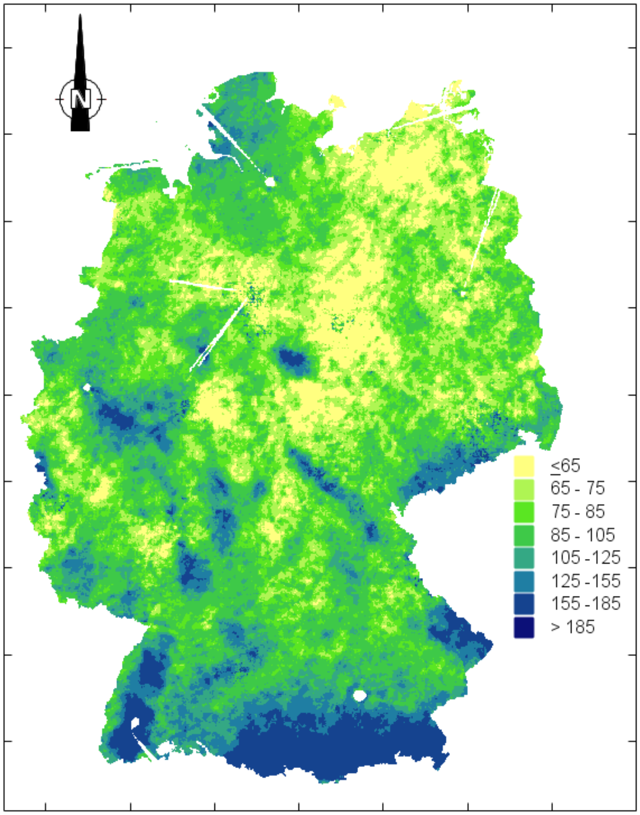


Figure ~~A2~~A4: ~~EAnnual erosivity~~ Annual average R-–factor map (N h^{-1} yr^{-1}) of Germany from 17 yr of radar rain data after winsorizing and removal of spokes but before kriging. Axes ticks represent distances of 100 km.

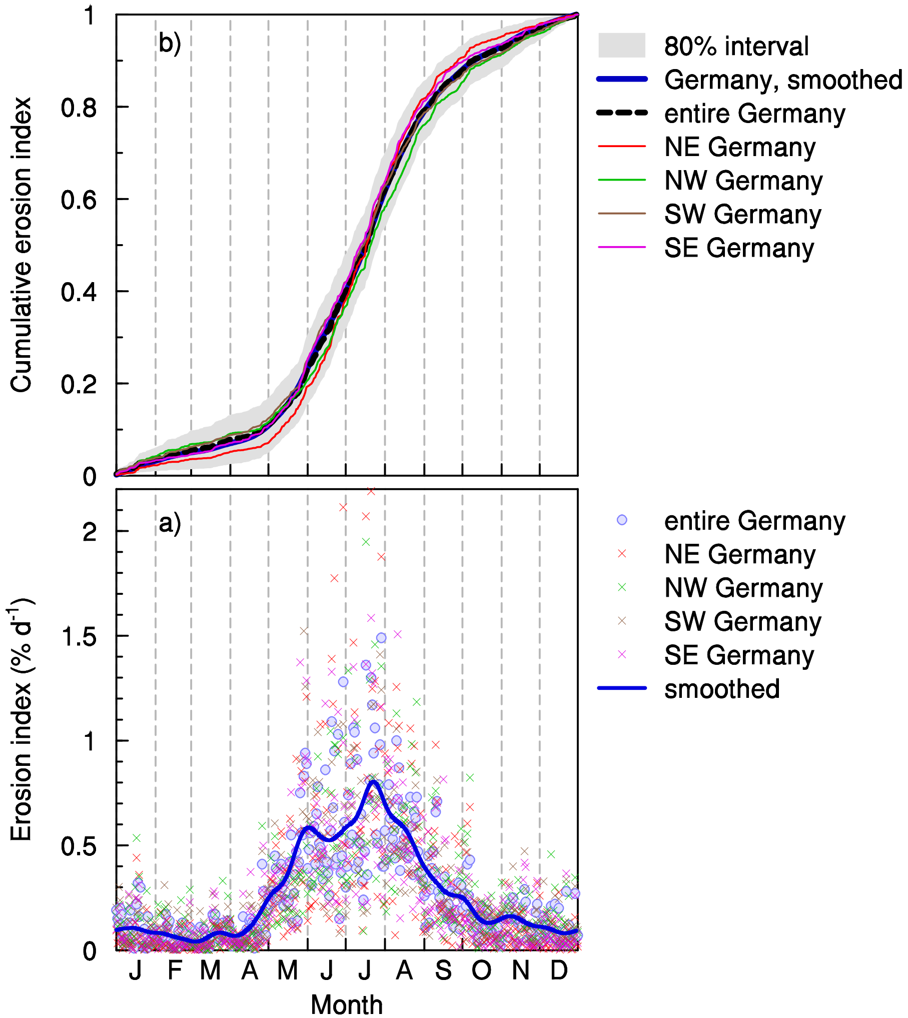


Figure A5: a) Measured (circles and crosses) and smoothed (solid blue line) daily erosion index from radar data. The crosses depict the values of the NE, NW, SW and SE quadrant of Germany. The NE quadrant is drier, more continental and at lower altitude than the German average; the NW quadrant has more maritime climate and is at lower altitude; the SE quadrant is wetter, more continental and at higher altitude; the SW quadrant is similar to average.

b) Cumulative distribution curves of measured daily erosion index for entire Germany and its four quadrants and smoothed erosion index for entire Germany.

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties

County (Landkreis)	Identifier	Size (km²)	Mean R
Ahrweiler	07131001	789	74.3
Aichach-Friedberg	09771111	780	109.9
Alb-Donau-Kreis	08425002	1358	103.4
Altenburger Land	16077001	570	90.5
Altenkirchen (Westerwald)	07132001	643	100.4
Altmarkkreis Salzwedel	15081026	2304	62.2
Altötting	09171111	569	128.9
Alzey-Worms	07331001	589	68.7
Amberg	09361000	50	81.0
Amberg-Sulzbach	09371111	1255	92.2
Ammerland	03451001	731	80.6
Anhalt-Bitterfeld	15082005	1461	68.0
Ansbach	09561000	2073	80.8
Aschaffenburg	09661000	762	118.7
Augsburg	09761000	1218	123.3
Aurich	03452001	1298	85.0
Bad Dürkheim	07332001	595	88.4
Bad Kissingen	09672111	1138	84.9
Bad Kreuznach	07133001	866	80.5
Bad Tölz-Wolfratshausen	09173111	1112	257.1
Baden-Baden. Stadtkreis	08211000	140	131.2
Bamberg	09461000	1222	85.5
Barnim	12060005	1481	72.7
Bautzen	14625010	2397	86.9
Bayreuth	09462000	1341	108.0
Berchtesgadener Land	09172111	840	250.0
Bergstraße	06431001	720	120.7
Berlin. Stadt	11000000	892	73.2
Bernkastel-Wittlich	07231001	1173	89.5
Biberach	08426001	1411	129.8
Bielefeld. Stadt	05711000	259	94.4
Birkenfeld	07134001	779	98.1
Böblingen	08115001	618	96.2
Bochum. Stadt	05911000	145	103.7
Bodenseekreis	08435005	666	149.3
Bonn. Stadt	05314000	142	94.5
Börde	15083020	2377	58.4
Borken	05554004	1426	94.4
Bottrop. Stadt	05512000	101	109.6
Brandenburg an der Havel. Stadt	12051000	229	78.8
Braunschweig. Stadt	03101000	192	69.3
Breisgau-Hochschwarzwald	08315003	1380	163.9

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Bremen. Stadt	04011000	326	78.0
Bremerhaven. Stadt	04012000	94	86.4
Burgenlandkreis	15084012	1419	77.0
Calw	08235006	798	105.6
Celle	03351001	1551	70.8
Cham	09372112	1527	106.1
Chemnitz. Stadt	14511000	221	107.5
Cloppenburg	03453001	1424	80.5
Coburg	09463000	639	82.4
Cochem-Zell	07135001	695	80.0
Coesfeld	05558004	1115	93.1
Cottbus. Stadt	12052000	165	74.0
Cuxhaven	03352002	2062	99.6
Dachau	09174111	580	115.1
Dahme-Spreewald	12061005	2277	79.2
Darmstadt. Wissenschaftsstadt	06411000	123	102.3
Darmstadt-Dieburg	06432001	659	91.5
Deggendorf	09271111	861	118.8
Delmenhorst. Stadt	03401000	63	69.6
Dessau-Roßlau. Stadt	15001000	246	65.0
Diepholz	03251001	1993	69.9
Dillingen a.d.Donau	09773111	792	94.7
Dingolfing-Landau	09279112	877	90.8
Dithmarschen	01051001	1444	122.5
Donau-Ries	09779111	1275	87.9
Donnersbergkreis	07333001	646	89.5
Dortmund. Stadt	05913000	280	88.7
Dresden. Stadt	14612000	328	96.9
Duisburg. Stadt	05112000	234	87.2
Düren	05358004	944	80.0
Düsseldorf. Stadt	05111000	218	75.6
Ebersberg	09175111	550	154.0
Eichsfeld	16061001	943	68.4
Eichstätt	09176111	1214	91.0
Eifelkreis Bitburg-Prüm	07232001	1634	82.0
Eisenach. Stadt	16056000	105	72.1
Elbe-Elster	12062024	1901	74.7
Emden. Stadt	03402000	112	73.3
Emmendingen	08316002	682	152.6
Emsland	03454001	2891	81.0
Ennepe-Ruhr-Kreis	05954004	412	116.1
Enzkreis	08236004	574	94.5
Erding	09177112	871	113.8

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Erfurt. Stadt	16051000	270	74.5
Erlangen	09562000	78	81.9
Erlangen-Höchstadt	09572111	565	80.2
Erzgebirgskreis	14521010	1827	136.9
Essen. Stadt	05113000	211	113.5
Esslingen	08116004	640	109.5
Euskirchen	05366004	1255	82.3
Flensburg. Stadt	01001000	57	108.8
Forchheim	09474119	643	98.3
Frankenthal (Pfalz). kreisfreie Stadt	07311000	44	80.3
Frankfurt (Oder). Stadt	12053000	148	89.6
Frankfurt am Main. Stadt	06412000	249	94.2
Freiburg im Breisgau. Stadtkreis	08311000	155	139.1
Freising	09178113	798	107.1
Freudenstadt	08237002	873	160.4
Freyung-Grafenau	09272116	985	175.0
Friesland	03455007	619	85.5
Fulda	06631001	1382	85.6
Fürstenfeldbruck	09179111	435	133.2
Fürth	09563000	371	78.3
Garmisch-Partenkirchen	09180112	1012	215.8
Gelsenkirchen. Stadt	05513000	106	108.9
Gera. Stadt	16052000	152	78.2
Germersheim	07334001	464	90.3
Gießen	06531001	857	88.0
Gifhorn	03151001	1570	72.1
Göppingen	08117001	643	119.3
Görlitz	14626010	2113	96.8
Goslar	03153002	969	122.9
Gotha	16067003	936	82.2
Göttingen	03159001	1756	92.2
Grafschaft Bentheim	03456001	985	80.6
Greiz	16076003	846	84.2
Groß-Gerau	06433001	454	73.4
Günzburg	09774111	764	112.4
Gütersloh	05754004	971	79.6
Hagen. Stadt der FernUniversität	05914000	161	104.8
Halle (Saale). Stadt	15002000	136	78.3
Hamburg. Freie und Hansestadt	02000000	753	87.7
Hameln-Pyrmont	03252001	799	79.0
Hamm. Stadt	05915000	228	77.6
Harburg	03353001	1250	88.4
Harz	15085040	2108	73.0

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Haßberge	09674111	957	83.4
Havelland	12063036	1728	74.5
Heidekreis	03358001	1883	80.3
Heidelberg. Stadtkreis	08221000	109	124.1
Heidenheim	08135010	628	99.8
Heilbronn	08125001	1100	90.5
Heilbronn. Stadtkreis	08121000	101	79.9
Heinsberg	05370004	630	71.1
Helmstedt	03154001	676	61.0
Herford	05758004	451	89.9
Herne. Stadt	05916000	52	104.6
Hersfeld-Rotenburg	06632001	1099	76.6
Herzogtum Lauenburg	01053001	1263	78.6
Hildburghausen	16069001	938	90.1
Hildesheim	03254002	1208	74.4
Hochsauerlandkreis	05958004	1963	107.5
Hochtaunuskreis	06434001	482	108.3
Hof	09464000	952	95.5
Hohenlohekreis	08126011	778	97.5
Holzminden	03255001	695	84.1
Höxter	05762004	1202	80.5
Ilm-Kreis	16070001	844	97.1
Ingolstadt	09161000	134	90.5
Jena. Stadt	16053000	115	79.0
Jerichower Land	15086005	1589	69.9
Kaiserslautern	07335002	642	97.5
Kaiserslautern. kreisfreie Stadt	07312000	141	100.7
Karlsruhe	08215007	1086	90.8
Karlsruhe. Stadtkreis	08212000	174	98.7
Kassel	06633001	1296	69.7
Kassel. documenta-Stadt	06611000	105	66.7
Kaufbeuren	09762000	40	168.0
Kelheim	09273111	1065	91.9
Kempten (Allgäu)	09763000	63	222.1
Kiel. Landeshauptstadt	01002000	120	92.5
Kitzingen	09675111	684	81.1
Kleve	05154004	1238	98.9
Koblenz. kreisfreie Stadt	07111000	106	80.2
Köln. Stadt	05315000	408	91.3
Konstanz	08335001	819	121.1
Krefeld. Stadt	05114000	137	83.1
Kronach	09476145	652	107.4
Kulmbach	09477117	658	100.4

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Kusel	07336001	575	101.2
Kyffhäuserkreis	16065001	1038	61.5
Lahn-Dill-Kreis	06532001	1067	102.7
Landau in der Pfalz. kreisfreie Stadt	07313000	83	104.7
Landkreis Rostock	13072001	3429	59.5
Landsberg am Lech	09181111	804	156.0
Landshut	09261000	1414	103.9
Leer	03457002	1089	72.8
Leipzig	14729010	1652	79.9
Leipzig. Stadt	14713000	299	87.6
Leverkusen. Stadt	05316000	79	98.0
Lichtenfels	09478111	520	80.7
Limburg-Weilburg	06533001	740	95.0
Lindau (Bodensee)	09776111	323	306.6
Lippe	05766004	1247	99.9
Lörrach	08336004	809	182.7
Lübeck. Hansestadt	01003000	212	76.1
Lüchow-Dannenberg	03354001	1227	73.6
Ludwigsburg	08118001	687	88.6
Ludwigshafen am Rhein. kreisfreie Stadt	07314000	78	87.5
Ludwigslust-Parchim	13076001	4768	71.8
Lüneburg	03355001	1327	80.4
Magdeburg. Landeshauptstadt	15003000	201	54.2
Main-Kinzig-Kreis	06435001	1398	110.4
Main-Spessart	09677114	1323	95.1
Main-Tauber-Kreis	08128006	1306	93.8
Main-Taunus-Kreis	06436001	222	102.2
Mainz. kreisfreie Stadt	07315000	98	68.4
Mainz-Bingen	07339001	607	68.8
Mannheim. Stadtkreis	08222000	145	92.9
Mansfeld-Südharz	15087010	1456	66.8
Marburg-Biedenkopf	06534001	1264	83.0
Märkischer Kreis	05962004	1064	121.3
Märkisch-Oderland	12064009	2159	80.6
Mayen-Koblenz	07137001	819	69.6
Mecklenburgische Seenplatte	13071001	5496	67.2
Meißen	14627010	1458	76.5
Memmingen	09764000	70	157.0
Merzig-Wadern	10042111	559	108.4
Mettmann	05158004	409	101.9
Miesbach	09182111	867	281.4
Miltenberg	09676111	716	105.2
Minden-Lübbecke	05770004	1153	77.0

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Mittelsachsen	14522010	2115	102.9
Mönchengladbach. Stadt	05116000	171	76.8
Mühldorf a.Inn	09183112	805	110.8
Mülheim an der Ruhr. Stadt	05117000	92	101.4
München	09184112	664	161.1
München. Landeshauptstadt	09162000	311	149.4
Münster. Stadt	05515000	304	88.9
Neckar-Odenwald-Kreis	08225001	1127	104.4
Neuburg-Schrobenhausen	09185113	740	93.8
Neumarkt i.d.OPf.	09373112	1345	92.8
Neumünster. Stadt	01004000	71	100.2
Neunkirchen	10043111	249	117.5
Neustadt a.d.Aisch-Bad Windsheim	09575112	1268	81.8
Neustadt a.d.Waldnaab	09374111	1428	88.8
Neustadt an der Weinstraße. kreisfreie Stadt	07316000	118	92.1
Neu-Ulm	09775111	516	121.0
Neuwied	07138002	629	80.4
Nienburg (Weser)	03256001	1403	66.6
Nordfriesland	01054001	2090	101.3
Nordhausen	16062002	714	63.2
Nordsachsen	14730010	2028	73.1
Nordwestmecklenburg	13074001	2125	68.6
Northeim	03155001	1270	81.7
Nürnberg	09564000	188	82.7
Nürnberger Land	09574111	798	103.9
Oberallgäu	09780112	1529	315.6
Oberbergischer Kreis	05374004	920	144.4
Oberhausen. Stadt	05119000	78	103.9
Oberhavel	12065036	1808	71.3
Oberspreewald-Lausitz	12066008	1224	75.4
Odenwaldkreis	06437001	626	124.6
Oder-Spree	12067024	2259	81.0
Offenbach	06438001	357	83.0
Offenbach am Main. Stadt	06413000	45	88.5
Oldenburg	03458001	1067	73.1
Oldenburg (Oldenburg). Stadt	03403000	104	78.8
Olpe	05966004	713	124.0
Ortenaukreis	08317001	1864	137.3
Osnabrück	03459001	2125	83.1
Osnabrück. Stadt	03404000	120	85.0
Ostalbkreis	08136002	1511	106.0
Ostallgäu	09777111	1394	215.5
Osterholz	03356001	654	84.5

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Ostholstein	01055001	1394	77.3
Ostprignitz-Ruppin	12068052	2526	77.0
Paderborn	05774004	1248	91.8
Passau	09262000	1600	121.0
Peine	03157001	536	65.8
Pfaffenhofen a.d.Ilm	09186113	761	100.8
Pforzheim. Stadtkreis	08231000	98	89.3
Pinneberg	01056001	664	97.6
Pirmasens. kreisfreie Stadt	07317000	62	99.4
Plön	01057001	1084	83.3
Potsdam. Stadt	12054000	187	70.5
Potsdam-Mittelmark	12069017	2593	78.3
Prignitz	12070008	2139	69.6
Rastatt	08216002	740	126.3
Ravensburg	08436001	1633	178.3
Recklinghausen	05562004	763	100.3
Regen	09276111	975	164.4
Regensburg	09362000	1473	84.4
Region Hannover	03241001	2299	70.8
Regionalverband Saarbrücken	10041100	413	103.7
Remscheid. Stadt	05120000	74	150.4
Rems-Murr-Kreis	08119001	858	119.4
Rendsburg-Eckernförde	01058001	2190	104.7
Reutlingen	08415014	1093	119.8
Rhein-Erft-Kreis	05362004	705	76.4
Rheingau-Taunus-Kreis	06439001	814	88.0
Rhein-Hunsrück-Kreis	07140001	994	84.1
Rheinisch-Bergischer Kreis	05378004	439	120.3
Rhein-Kreis Neuss	05162004	579	72.2
Rhein-Lahn-Kreis	07141001	783	87.8
Rhein-Neckar-Kreis	08226003	1062	114.3
Rhein-Pfalz-Kreis	07338001	305	88.5
Rhein-Sieg-Kreis	05382004	1155	96.8
Rhön-Grabfeld	09673113	1022	74.7
Rosenheim	09163000	1477	210.4
Rostock	13003000	181	68.4
Rotenburg (Wümme)	03357001	2075	92.6
Roth	09576111	895	84.9
Rottal-Inn	09277111	1281	102.6
Rottweil	08325001	771	115.4
Saale-Holzland-Kreis	16074001	816	85.5
Saalekreis	15088020	1440	73.1
Saale-Orla-Kreis	16075002	1152	84.8

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Saalfeld-Rudolstadt	16073001	1036	87.1
Saarlouis	10044111	461	105.3
Saarpfalz-Kreis	10045111	420	101.3
Sächsische Schweiz-Osterzgebirge	14628010	1654	111.7
Salzgitter. Stadt	03102000	225	73.6
Salzlandkreis	15089005	1435	61.5
Schaumburg	03257001	677	81.9
Schleswig-Flensburg	01059001	2072	106.8
Schmalkalden-Meiningen	16066001	1211	84.7
Schwabach	09565000	41	73.6
Schwäbisch Hall	08127008	1485	94.6
Schwalm-Eder-Kreis	06634001	1541	70.7
Schwandorf	09376112	1458	81.5
Schwarzwald-Baar-Kreis	08326003	1028	135.6
Schweinfurt	09662000	877	71.0
Schwerin	13004000	130	64.8
Segeberg	01060002	1346	92.6
Siegen-Wittgenstein	05970004	1136	121.3
Sigmaringen	08437005	1206	118.3
Soest	05974004	1332	88.1
Solingen. Klingenstadt	05122000	89	115.1
Sömmerda	16068001	807	64.6
Sonneberg	16072001	433	125.5
Speyer. kreisfreie Stadt	07318000	43	89.0
Spree-Neiße	12071028	1658	77.5
St. Wendel	10046111	478	122.4
Stade	03359001	1268	97.1
Städteregion Aachen	05334002	707	105.9
Starnberg	09188113	487	169.0
Steinburg	01061001	1057	107.7
Steinfurt	05566004	1800	95.6
Stendal	15090003	2437	64.5
Stormarn	01062001	766	87.6
Straubing	09263000	67	90.5
Straubing-Bogen	09278112	1201	103.8
Stuttgart. Stadtkreis	08111000	210	92.0
Südliche Weinstraße	07337001	641	104.2
Südwestpfalz	07340001	957	109.7
Suhl. Stadt	16054000	102	123.8
Teltow-Fläming	12072002	2104	73.0
Tirschenreuth	09377112	1085	96.5
Traunstein	09189111	1533	232.0
Trier. kreisfreie Stadt	07211000	116	77.3

Table A1. Mean erosivity ($N\ h^{-1}\ yr^{-1}$) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Trier-Saarburg	07235001	1109	92.8
Tübingen	08416006	521	114.2
Tuttlingen	08327002	735	124.3
Uckermark	12073008	3077	74.2
Uelzen	03360001	1463	79.2
Ulm. Stadtkreis	08421000	119	93.7
Unna	05978004	544	83.6
Unstrut-Hainich-Kreis	16064001	979	63.2
Unterallgäu	09778111	1230	161.8
Vechta	03460001	815	73.2
Verden	03361001	790	76.5
Viersen	05166004	566	78.0
Vogelsbergkreis	06535001	1460	95.3
Vogtlandkreis	14523010	1412	101.5
Vorpommern-Greifswald	13075001	3953	72.1
Vorpommern-Rügen	13073001	3213	66.2
Vulkaneifel	07233002	915	88.4
Waldeck-Frankenberg	06635001	1850	72.8
Waldshut	08337002	1133	166.8
Warendorf	05570004	1321	75.6
Wartburgkreis	16063003	1307	75.7
Weiden i.d.OPf.	09363000	71	91.7
Weilheim-Schongau	09190111	968	214.4
Weimar. Stadt	16055000	84	70.6
Weimarer Land	16071001	804	73.8
Weißenburg-Gunzenhausen	09577111	971	94.1
Werra-Meißner-Kreis	06636001	1025	73.9
Wesel	05170004	1046	92.7
Wesermarsch	03461001	830	77.9
Westerwaldkreis	07143001	992	100.5
Wetteraukreis	06440001	1102	97.0
Wiesbaden. Landeshauptstadt	06414000	204	79.4
Wilhelmshaven. Stadt	03405000	108	94.8
Wittenberg	15091010	1943	77.8
Wittmund	03462001	661	96.6
Wolfenbüttel	03158002	724	71.7
Wolfsburg. Stadt	03103000	205	66.3
Worms. kreisfreie Stadt	07319000	109	71.7
Wunsiedel i.Fichtelgebirge	09479111	606	92.9
Wuppertal. Stadt	05124000	169	128.8
Würzburg	09663000	1055	85.0
Zollernalbkreis	08417002	918	118.0

Table A1. Mean erosivity (N h^{-1} yr^{-1}) of all German counties (continued)

County (Landkreis)	Identifier	Size (km²)	Mean R
Zweibrücken. kreisfreie Stadt	07320000	71	90.4
Zwickau	14524010	950	102.4

Table A2. Daily erosion index

Date	Daily erosivity (%)	Erosivity since 1 Jan (%)	Date	Daily erosivity (%)	Erosivity since 1 Jan (%)	Date	Daily erosivity (%)	Erosivity since 1 Jan (%)	Date	Daily erosivity (%)	Erosivity since 1 Jan (%)
1 Jan	0.09	0.1	1 Feb	0.08	3.1	1 Mar	0.04	5.0	1 Apr	0.07	6.9
2 Jan	0.10	0.2	2 Feb	0.08	3.2	2 Mar	0.04	5.0	2 Apr	0.07	7.0
3 Jan	0.10	0.3	3 Feb	0.08	3.3	3 Mar	0.04	5.1	3 Apr	0.07	7.1
4 Jan	0.10	0.4	4 Feb	0.08	3.4	4 Mar	0.04	5.1	4 Apr	0.07	7.1
5 Jan	0.10	0.5	5 Feb	0.08	3.5	5 Mar	0.04	5.1	5 Apr	0.07	7.2
6 Jan	0.10	0.6	6 Feb	0.08	3.5	6 Mar	0.04	5.2	6 Apr	0.07	7.3
7 Jan	0.10	0.7	7 Feb	0.08	3.6	7 Mar	0.04	5.2	7 Apr	0.07	7.4
8 Jan	0.10	0.8	8 Feb	0.08	3.7	8 Mar	0.04	5.3	8 Apr	0.07	7.4
9 Jan	0.10	0.9	9 Feb	0.08	3.8	9 Mar	0.04	5.3	9 Apr	0.07	7.5
10 Jan	0.10	1.0	10 Feb	0.08	3.8	10 Mar	0.05	5.4	10 Apr	0.07	7.6
11 Jan	0.10	1.1	11 Feb	0.07	3.9	11 Mar	0.05	5.4	11 Apr	0.08	7.6
12 Jan	0.11	1.2	12 Feb	0.07	4.0	12 Mar	0.05	5.5	12 Apr	0.08	7.7
13 Jan	0.11	1.3	13 Feb	0.07	4.1	13 Mar	0.05	5.5	13 Apr	0.09	7.8
14 Jan	0.11	1.4	14 Feb	0.07	4.1	14 Mar	0.06	5.6	14 Apr	0.09	7.9
15 Jan	0.11	1.5	15 Feb	0.07	4.2	15 Mar	0.06	5.6	15 Apr	0.10	8.0
16 Jan	0.11	1.6	16 Feb	0.07	4.3	16 Mar	0.06	5.7	16 Apr	0.10	8.1
17 Jan	0.11	1.7	17 Feb	0.06	4.3	17 Mar	0.07	5.8	17 Apr	0.11	8.2
18 Jan	0.10	1.8	18 Feb	0.06	4.4	18 Mar	0.07	5.8	18 Apr	0.11	8.3
19 Jan	0.10	1.9	19 Feb	0.06	4.5	19 Mar	0.07	5.9	19 Apr	0.12	8.4
20 Jan	0.10	2.0	20 Feb	0.06	4.5	20 Mar	0.08	6.0	20 Apr	0.13	8.6
21 Jan	0.10	2.1	21 Feb	0.06	4.6	21 Mar	0.08	6.1	21 Apr	0.14	8.7
22 Jan	0.10	2.2	22 Feb	0.06	4.6	22 Mar	0.08	6.1	22 Apr	0.15	8.9
23 Jan	0.10	2.3	23 Feb	0.05	4.7	23 Mar	0.08	6.2	23 Apr	0.15	9.0
24 Jan	0.09	2.4	24 Feb	0.05	4.7	24 Mar	0.08	6.3	24 Apr	0.16	9.2
25 Jan	0.09	2.5	25 Feb	0.05	4.8	25 Mar	0.08	6.4	25 Apr	0.17	9.3
26 Jan	0.09	2.6	26 Feb	0.05	4.8	26 Mar	0.08	6.5	26 Apr	0.18	9.5
27 Jan	0.09	2.7	27 Feb	0.05	4.9	27 Mar	0.08	6.6	27 Apr	0.20	9.7
28 Jan	0.09	2.8	28 Feb	0.05	4.9	28 Mar	0.08	6.6	28 Apr	0.21	9.9
29 Jan	0.09	2.9				29 Mar	0.08	6.7	29 Apr	0.22	10.2
30 Jan	0.08	3.0				30 Mar	0.08	6.8	30 Apr	0.23	10.4
31 Jan	0.08	3.0				31 Mar	0.07	6.9			

Table A2. Daily erosion index (continued)

Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)	Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)	Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)	Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)
1 May	0.24	10.6	1 Jun	0.58	22.8	1 Jul	0.58	39.3	1 Aug	0.71	61.1
2 May	0.25	10.9	2 Jun	0.58	23.4	2 Jul	0.58	39.9	2 Aug	0.70	61.8
3 May	0.26	11.1	3 Jun	0.58	24.0	3 Jul	0.59	40.5	3 Aug	0.68	62.5
4 May	0.26	11.4	4 Jun	0.58	24.5	4 Jul	0.59	41.1	4 Aug	0.67	63.2
5 May	0.27	11.7	5 Jun	0.58	25.1	5 Jul	0.60	41.7	5 Aug	0.66	63.8
6 May	0.28	11.9	6 Jun	0.58	25.7	6 Jul	0.60	42.3	6 Aug	0.65	64.5
7 May	0.28	12.2	7 Jun	0.57	26.3	7 Jul	0.61	42.9	7 Aug	0.64	65.1
8 May	0.29	12.5	8 Jun	0.57	26.8	8 Jul	0.61	43.5	8 Aug	0.63	65.8
9 May	0.29	12.8	9 Jun	0.56	27.4	9 Jul	0.62	44.1	9 Aug	0.63	66.4
10 May	0.30	13.1	10 Jun	0.55	27.9	10 Jul	0.63	44.8	10 Aug	0.62	67.0
11 May	0.30	13.4	11 Jun	0.55	28.5	11 Jul	0.64	45.4	11 Aug	0.62	67.6
12 May	0.31	13.7	12 Jun	0.54	29.0	12 Jul	0.65	46.1	12 Aug	0.61	68.2
13 May	0.32	14.0	13 Jun	0.54	29.6	13 Jul	0.67	46.7	13 Aug	0.61	68.9
14 May	0.33	14.4	14 Jun	0.53	30.1	14 Jul	0.68	47.4	14 Aug	0.60	69.5
15 May	0.34	14.7	15 Jun	0.53	30.6	15 Jul	0.70	48.1	15 Aug	0.60	70.1
16 May	0.35	15.0	16 Jun	0.53	31.2	16 Jul	0.71	48.8	16 Aug	0.59	70.6
17 May	0.36	15.4	17 Jun	0.53	31.7	17 Jul	0.73	49.5	17 Aug	0.59	71.2
18 May	0.37	15.8	18 Jun	0.52	32.2	18 Jul	0.75	50.3	18 Aug	0.58	71.8
19 May	0.39	16.2	19 Jun	0.52	32.7	19 Jul	0.76	51.1	19 Aug	0.57	72.4
20 May	0.41	16.6	20 Jun	0.52	33.3	20 Jul	0.78	51.8	20 Aug	0.56	72.9
21 May	0.43	17.0	21 Jun	0.53	33.8	21 Jul	0.79	52.6	21 Aug	0.55	73.5
22 May	0.45	17.4	22 Jun	0.53	34.3	22 Jul	0.80	53.4	22 Aug	0.54	74.0
23 May	0.47	17.9	23 Jun	0.53	34.9	23 Jul	0.80	54.2	23 Aug	0.52	74.5
24 May	0.48	18.4	24 Jun	0.54	35.4	24 Jul	0.80	55.0	24 Aug	0.51	75.1
25 May	0.50	18.9	25 Jun	0.54	35.9	25 Jul	0.80	55.8	25 Aug	0.50	75.6
26 May	0.52	19.4	26 Jun	0.55	36.5	26 Jul	0.79	56.6	26 Aug	0.48	76.0
27 May	0.53	19.9	27 Jun	0.55	37.0	27 Jul	0.79	57.4	27 Aug	0.47	76.5
28 May	0.55	20.5	28 Jun	0.56	37.6	28 Jul	0.77	58.2	28 Aug	0.46	77.0
29 May	0.56	21.1	29 Jun	0.57	38.2	29 Jul	0.76	58.9	29 Aug	0.44	77.4
30 May	0.57	21.6	30 Jun	0.57	38.7	30 Jul	0.74	59.7	30 Aug	0.43	77.8
31 May	0.58	22.2				31 Jul	0.73	60.4	31 Aug	0.42	78.3

Table A2. Daily erosion index (continued)

Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)	Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)	Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)	Date	Daily erosi-vity (%)	Erosi-vity since 1 Jan (%)
1 Sep	0.41	78.7	1 Oct	0.25	87.8	1 Nov	0.15	93.0	1 Dec	0.11	97.2
2 Sep	0.40	79.1	2 Oct	0.25	88.0	2 Nov	0.15	93.1	2 Dec	0.11	97.3
3 Sep	0.39	79.4	3 Oct	0.25	88.3	3 Nov	0.15	93.3	3 Dec	0.11	97.4
4 Sep	0.38	79.8	4 Oct	0.24	88.5	4 Nov	0.16	93.4	4 Dec	0.11	97.5
5 Sep	0.37	80.2	5 Oct	0.23	88.8	5 Nov	0.16	93.6	5 Dec	0.11	97.6
6 Sep	0.36	80.6	6 Oct	0.23	89.0	6 Nov	0.16	93.7	6 Dec	0.11	97.7
7 Sep	0.35	80.9	7 Oct	0.22	89.2	7 Nov	0.16	93.9	7 Dec	0.11	97.9
8 Sep	0.35	81.3	8 Oct	0.21	89.4	8 Nov	0.16	94.1	8 Dec	0.11	98.0
9 Sep	0.34	81.6	9 Oct	0.20	89.6	9 Nov	0.16	94.2	9 Dec	0.10	98.1
10 Sep	0.33	81.9	10 Oct	0.19	89.8	10 Nov	0.16	94.4	10 Dec	0.10	98.2
11 Sep	0.33	82.3	11 Oct	0.18	90.0	11 Nov	0.16	94.5	11 Dec	0.10	98.3
12 Sep	0.32	82.6	12 Oct	0.17	90.2	12 Nov	0.16	94.7	12 Dec	0.10	98.4
13 Sep	0.31	82.9	13 Oct	0.17	90.3	13 Nov	0.16	94.9	13 Dec	0.09	98.5
14 Sep	0.31	83.2	14 Oct	0.16	90.5	14 Nov	0.15	95.0	14 Dec	0.09	98.6
15 Sep	0.30	83.5	15 Oct	0.15	90.6	15 Nov	0.15	95.2	15 Dec	0.09	98.6
16 Sep	0.29	83.8	16 Oct	0.15	90.8	16 Nov	0.15	95.3	16 Dec	0.09	98.7
17 Sep	0.29	84.1	17 Oct	0.14	90.9	17 Nov	0.15	95.5	17 Dec	0.09	98.8
18 Sep	0.28	84.4	18 Oct	0.14	91.1	18 Nov	0.14	95.6	18 Dec	0.08	98.9
19 Sep	0.28	84.6	19 Oct	0.13	91.2	19 Nov	0.14	95.7	19 Dec	0.08	99.0
20 Sep	0.27	84.9	20 Oct	0.13	91.3	20 Nov	0.13	95.9	20 Dec	0.08	99.1
21 Sep	0.27	85.2	21 Oct	0.13	91.5	21 Nov	0.13	96.0	21 Dec	0.08	99.1
22 Sep	0.27	85.4	22 Oct	0.13	91.6	22 Nov	0.13	96.1	22 Dec	0.08	99.2
23 Sep	0.26	85.7	23 Oct	0.13	91.7	23 Nov	0.13	96.3	23 Dec	0.08	99.3
24 Sep	0.26	86.0	24 Oct	0.13	91.9	24 Nov	0.12	96.4	24 Dec	0.08	99.4
25 Sep	0.26	86.2	25 Oct	0.13	92.0	25 Nov	0.12	96.5	25 Dec	0.08	99.5
26 Sep	0.26	86.5	26 Oct	0.13	92.1	26 Nov	0.12	96.6	26 Dec	0.08	99.6
27 Sep	0.26	86.8	27 Oct	0.13	92.2	27 Nov	0.12	96.7	27 Dec	0.09	99.6
28 Sep	0.26	87.0	28 Oct	0.14	92.4	28 Nov	0.12	96.9	28 Dec	0.09	99.7
29 Sep	0.26	87.3	29 Oct	0.14	92.5	29 Nov	0.11	97.0	29 Dec	0.09	99.8
30 Sep	0.26	87.5	30 Oct	0.14	92.7	30 Nov	0.11	97.1	30 Dec	0.09	99.9
			31 Oct	0.14	92.8				31 Dec	0.09	100.0