Dynamic Rainfall Erosivity Estimates Derived from GPM IMERG data

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Abstract.

Soil degradation is a critical threat to agriculture and food security around the world. Understanding the processes that drive
10   soil erosion is necessary to support sustainable management practices and to reduce eutrophication of water systems from fertilizer runoff. The erosivity of precipitation is a primary control on the rate of soil erosion, but to calculate erosivity high frequency precipitation data is required. Prior global scale analysis has almost exclusively used ground-based rainfall gauges to calculate erosivity, but the advent of high frequency satellite rainfall data provides an opportunity to estimate erosivity using globally consistent gridded satellite rainfall. In this study, I have tested the use of GPM IMERG rainfall data to calculate global
15   rainfall erosivity. I have tested three different approaches to assess whether simplification of IMERG data allows for robust calculation of erosivity, finding that the highest frequency 30-minute data is needed to best replicate gauge-based estimates. I also find that in areas where ground-based gauges are sparse, there is more disparity between the IMERG derived estimates and the ground-based results, suggesting that IMERG may allow for improved erosivity estimates in data-poor areas. The global extent and accessibility of IMERG data allows for regular calculation of erosivity on a month-to-month timeframe,
20   permitting improved dynamic characterisation of rainfall erosivity across the world in near-real time. These results demonstrate the value of satellite data to assess the impact of rainfall on soil erosion and may benefit practitioners of sustainable land management planning.

1 Introduction

Topsoil is a key component of the Earth's critical zone, acting to sequester carbon, filter pollutants from water, and supporting
25   growth of plants. Agricultural topsoil in particular is the fundamental basis upon which food security relies, and sustainable management of topsoil is one of the defined UN sustainable development goals [UN, 2015]. However, land management practices around the world have led to significant degradation of topsoils, with global analyses suggesting that the "majority of soils are in only fair, poor, or very poor condition" [FAO, 2015]. Soil degradation threatens communities around the world with food insecurity in the next decades, alongside limits to water supply for irrigation [Hanjra & Qureshi, 2010]. Across large
30   parts of global agricultural zones, the rate of topsoil loss far exceeds the replenishment rate [FAO, 2015]. Soil loss costs

hundreds of billions of dollars each year [GSP, 2017] and given that it may lead to significant declines in productive agricultural land area by 2050, preservation of topsoil is essential to ensure a sustainable future [Steffen et al. 2015].

Degradation of soil is driven by many factors, but a key driver is liquid precipitation. Rainfall washes off loose soil and determining the erosivity of rainfall is a major component of soil loss calculations. The widely used Revised Universal Soil

35 Loss equation [Renard, 1997, USDA, 2013] incorporates rainfall erosivity as the main dynamic factor determining soil loss. Calculating and measuring rainfall erosivity is therefore imperative to support models and observations of soil degradation. Some global scale analyses have relied upon ground-based rainfall gauges to provide observations of rainfall intensity and duration [Panagos 2015, Yin et al. 2017], including the widely used Global Rainfall Erosivity Database (GloREDa, Panagos et al. 2017), but there is major geographic variability in the availability of rainfall gauge data around the world [Panagos et al.

40 2017], and gauge sparsity is particularly pronounced for gauges that record at sufficient temporal frequency to characterise erosivity. Recent studies have utilized satellite rainfall data to provide spatially consistent estimates of erosivity, filling in gaps in areas that are sparse in terms of ground-based gauges. Bezak and coauthors [2022] have used data from the National Oceanic and Atmospheric Administration (NOAA) Climate Data Record (CDR) Climate Prediction Center MORPHing (CMORPH) dataset, which offers global scale data at a 30-minute resolution. Li et al. [2017] utilized the Tropical Rainfall Measurement

45 Mission (TRMM) data to estimate erosion, but this data is only available at 3-hour resolution, which is not widely considered to be sufficiently high frequency to reliably estimate erosivity.

In this study, I use the 30-minute data from the NASA IMERG (Integrated Multi-satellitE Retrievals for GPM (Global Precipitation Mission)) dataset, which covers the time period from 2000 until present, to estimate rainfall erosivity at a global scale. These estimates provide informative comparisons to the study of Bezak and coauthors [2022]. I have also tested several

50 approaches to calculate erosivity from rainfall-time series, and the comparison with the ground based GloREDa dataset [Panagos et al. 2017] provide insight into the value of high temporal frequency rainfall data for erosivity estimation. This application of IMERG data provides an additional method for calculating erosivity at a global scale and allows for dynamic estimates of erosivity at various time intervals, depending on the calculation method chosen.

2 Methods

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2.1 Rainfall Data

In this study, three methods employed in previous studies are employed to calculate rainfall erosivity using the IMERG rainfall dataset. IMERG version 6B is the latest version of the long-running IMERG rainfall dataset [Huffman et al. 2019]. IMERG utilizes observations from several different satellites to estimate precipitation across most of the surface of Earth. The IMERG

60 algorithm uses microwave observations from the Global Precipitation Monitoring (GPM) satellite (2014-present) and also the earlier Tropical Rainfall Measuring Mission (TRMM) satellite (2000-2015). Microwave observations are included from a range of other satellites, and a series of merging methods are used to interpolate between these observations [Joyce et al. 2011, Huffman et al. 2011, Hong et al. 2004], including the CMORPH-KF algorithm [Joyce et al. 2011]. Infra-red observations are also used to support the interpolation of results [Huffman et al. 2019]. While a near-real time product is available, the research

65   grade IMERG 'final' uses data from the Global Precipitation Climatology Center (GPCC) ground-based gauges to correct the
      initial 'early' results. In this study, I use the 'final' IMERG v06B product, at three different temporal resolutions: monthly, 3-
      hourly, and the highest frequency 30-minute product. All three of these are available from 2000-present, but since the algorithm
      processing starts after January 1st, 2000, I have started the analysis from January 1st, 2001-December 31st, 2021. IMERG has
      a grid cell of 0.1 decimal degrees (approximately 9km at the equator) and so all erosivity outputs maintain this grid cell size.

70   IMERG v06B does distinguish between liquid and non-liquid precipitation (rain and snow), and I use the estimate of liquid
      precipitation proportion to calculate only the liquid precipitation. Although across most the latitude range studied here (60
      degrees N – 60 degrees S) rainfall, rather than snow, is the dominant precipitation type, but since rainfall is the key type of
      precipitation that determines erosion of surface material I suggest it is essential to perform this correction to exclude non-liquid
      precipitation when calculating rainfall totals.

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2.2 Calculating Rainfall Erosivity

Rainfall erosivity depends on both the intensity and duration of rainfall in a given location. The United States Department of
Agriculture (USDA) has developed the Revised Universal Soil Loss Equation (RUSLE) which utilizes rainfall erosivity as a
key factor [USDA, 2013]. The relationships developed for RUSLE have been widely tested and are considered the standard

80   set of equations to determine erosivity from ground-based data. The most recently revised version of the RUSLE model
      [USDA, 2013] converts rainfall into erosivity using the following series of steps. First, the rainfall time-series is divided into
      specific storm events, each separated by periods of 6 hours or greater where rainfall was less than 1.27mm. Rainfall events
      with less total rainfall than 12.7mm (0.5 in) are excluded from calculations [Brown and Foster 1987]; this was initially to
      reduce computational load, but studies have shown that rainfall events with lower totals than this do not significantly contribute

85   to overall erosivity.

Once the rainfall events have been isolated, the specific kinetic energy e_k (units of MJ ha^{-1} mm^{-1}) is calculated. Different
studies have used a variety of coefficients for this equation; in this study, I have used the current USDA RUSLE 2 model
coefficients [USDA, 2013]. I have also tested the older RUSLE 1 coefficients for comparison with older studies for one of the
rainfall erosivity calculation approaches, with limited differences observed. The RUSLE 2 equation is as follows:

90    $e_k = 0.29 . [1 - 0.72 . e^{(-0.082 . I)}]$ (Equation 1)

Where I is rainfall intensity in mm.h^{-1}. To calculate erosivity, first the total kinetic energy of the rainfall event is calculated:

$E = e_k . I . \Delta t$ (Equation 2)

Where E is the total kinetic energy and Δt is the time interval in hours. The erosivity is then calculated:

$R = \frac{\sum_n E . I_{30}}{N}$ (Equation 3)

95   Where I_{30} is the maximum 30-minute rainfall intensity of rainfall event n, which occurred over a time span of N years. R
      therefore has units of MJ.mm ha^{-1} h^{-1} yr^{-1}.

Using these equations, and the separation of the rainfall record into storms as described above, I have calculated R from the 30-minute IMERG rainfall record from January 2001 until December 2021. This provides a single value for R in the 3600x1800 cells of the IMERG record, which I have then reduced to only global land areas between 60 degrees N and 60 degrees S, to exclude areas where the IMERG record is incomplete. Additionally, I have calculated the monthly values for R for the year 2020, to demonstrate the applicability of this method to estimate erosivity dynamically.

This approach has been successfully and widely used with ground-based gauge analysis of erosivity using the RUSLE model since 1987, but alternative approaches have also been developed. Earlier iterations of satellite rainfall products from the TRMM satellite constellation were available only at a 3-hour time interval, which precluded calculation of 30-minute intensity. Prior studies utilizing TRMM products to calculate erosivity have used two other methods; the Modified Fournier Index (MFI), and by considering each 3-hourly rainfall window as an individual storm [Vrieling et al. 2010]. Because analysing 20 years of 30-minute IMERG data is computationally intensive (over 9TB of data are analysed in total), I have also tested these two methods using global IMERG data to assess compare their performance would warrant the use of these simplified approaches. I have also used the 30-minute IMERG data to calculate R according to equations 1-3 above. The details for the MFI and 3-hour storm approaches are described next.

The Fournier Index [Fournier, 1960] was an early model to describe rainfall erosivity that relied on only low-frequency recording of rainfall. It is defined as:

$$FI = \frac{p^2}{P} \hspace{3cm} \text{(Equation 4)}$$

Where p is the average rainfall of the month with the highest rainfall, and P is the average annual rainfall. Arnoldus [1977] revised this index to create the Modified Fournier Index (MFI), defined as follows:

$$MFI = \frac{1}{P} \sum_{i=1}^{12} p_i^2 \hspace{3cm} \text{(Equation 5)}$$

Where p_i is the average rainfall in month i. Arnoldus [1977] demonstrated significantly better agreement between short-term rainfall observations of erosivity and the MFI values than FI values, and it has been used by other authors since [Renard and Freimund, 1994], including with satellite rainfall data [Vrieling et al. 2010]. The units for both of these indices are mm (mm^2/mm), and prior studies have demonstrated it is most effective when applied to homogenous climatic regions. To convert between MFI and R values, various strategies have been applied, with different coefficients derived for various climatic zones. Disagreement remains in the literature surrounding the appropriate equations to use, and which exact units were used by Arnoldus [1977] (see Majhi et al. [2022], Chen & Bezak [2022], Mahji et al. [2021], Renard and Freimund [1994]). In this study I have not converted the raw MFI values, since the intention is to contrast the relative correlations with the R factor estimates from higher frequency rainfall data and ground-based analyses. Given the relative limitations to the MFI calculation (see below), the alternative methods presented here may offer more promising solutions for future studies. Nevertheless, MFI values are widely used and still maintain some advantages, in particular given their relatively low computational level and applicability to more temporally sparse data. I have calculated MFI values both for the entire IMERG record, as well as the interannual variability.

130   Vrieling and coauthors [2010] tested an alternative method to calculate R using 3-hour satellite rainfall data, prior to the advent of the 30-minute IMERG rainfall data. The specific kinetic energy of rainfall is defined as in equation 1 (although Vrieling et al. [2010] use different coefficients). Because of the lower temporal resolution of the 3-hour data, under this approach it is not considered justified to define the start and end of a storm event in the rainfall records. As such, each 3-hour window is considered as a storm event, and the kinetic energy for each 3-hour window is calculated as such:

135   $E3h = e_k \times 3I$ (Equation 6)

With I meaning the rainfall intensity, in mm.h^{-1}. To calculate R according to equation 3, the maximum 30-minute intensity of the storm is required, but since that information is unavailable with the 3-hourly data, Vrieling et al. [2010] used the average intensity of the 3-hour rainfall period as a multiplier. However, with the 30-minute IMERG data, I am able to calculate the maximum in each 3-hour window, so in this estimate, R is defined as:

140   $R = \sum_{k=1}^{N} E3h_k \times I30_k$ (Equation 7)

As with the 30-minute version, the units are: MJ.mm ha^{-1} h^{-1} yr^{-1}, and as such these estimates are directly comparable with those of the 30-minute estimates, as well as ground-based estimates. Since several published estimates for the coefficients for specific kinetic energy are available, I have tested the RUSLE 2, RUSLE 1, and Vrieling et al [2010] coefficients for this estimate of R. This is because the lower computational requirement of this estimate allows for testing of multiple coefficients.

145   These are discussed below.

2.3 Ground-based comparison

Rainfall erosivity analysis has typically been conducted at a local or regional scale, but fortunately recent work by Panagos and coauthors [2017] derived the first global scale erosivity estimate, the Global Erosivity Database (GloREDa). This model

150   uses 3625 ground-based stations, with rainfall records averaging 17 years, to calculate a global estimate of erosivity based on the equations described above (equations 1, 2 and 3) and using a Gaussian regression model to interpolate between stations. The density of stations significantly varies, with 48% in Europe, and only 5% in South America and Africa. I have used the GloREDa data as an independent comparison for the IMERG-derived erosivity estimates for this study. The GloREDa estimates are available at a higher spatial resolution (30 arc-seconds) than the IMERG derived estimates, so I have

155   downsampled the GloREDa data to the native IMERG resolution (0.1 degrees) using a bilinear interpolation method. This avoids creating additional data from the IMERG-based approaches. I compare the results of the IMERG and GloREDa estimates both at a cell-by-cell scale but also in terms of overall statistics, including mean, median and standard deviation values.

160   ## 3 Results

3.1 30 Minute Erosivity

The 20-year average erosivity values estimated using IMERG 30-minute rainfall data are shown in Figure 1, part A. The global map highlights critical hotspots for rainfall erosivity, as well as areas where low rainfall levels lead to very low erosivity.

Significant areas where erosivity is elevated include the areas of Central America and the Northern part of South America, the Himalayas (with particularly high rates in the Indus-Yarlung Suture Zone at the Eastern Himalayan Syntaxis), the Indonesian Archipelago and Papua New Guinea, and Bangladesh. Low erosivity values are estimated for much of the global desert regions, with a broad belt of low erosivity spreading from the Western Sahara, across the Arabian Peninsula, through into Southern Siberia. An interesting emergent trend is for very high erosivity values in some coastal areas, including the Sub-Andean coast of Colombia; the Pacific North-West of the United States and Canada; the coasts of Guinea-Bissau, Guinea and Sierra Leone; the Western Ghats of India; and much of the Bangladeshi-Myanmar coast. Many of these coastal zones are impacted by infrequent but extreme tropical storm rainfall events, and it is possible that these contribute to the high erosivity values calculated in these areas.

3.2 Alternative Erosivity Estimates from IMERG

The IMERG-derived erosivity estimates calculated for the 3-hour and MFI storm approaches are shown in parts B and C of Figure 1. While the overall global patterns are broadly similar to those produced by the 30-minute version (Figure 1A), including the trend of high erosivity values observed in many coastal areas, the absolute values differ quite significantly. While the MFI values (Figure 1B) are not directly comparable to the R values calculated via the other metrics, prior studies have suggested a non-linear scaling relationship with exponents of ~1.5 [Arnoldus, 1977], the large spread of values observed when comparing cell-by-cell values for the MFI and 30-minute R values (Figure 2A) do not support a single, consistent scaling relation. Instead, this likely supports a scaling relationship dependent on local climatic conditions, as has been emphasized by other authors.

The values obtained with the 3-hour storm model (Figure 1B) are directly comparable to the 30-minute version since they have the same units. As with the MFI values, the overall patterns that emerge globally are similar, but once again there are differences in absolute values. The Pearson correlation coefficient of the cell-by-cell values of the 30-minute and 3-hour estimates is high ($R^2 = 0.923$), but this is not a perfect correlation, nor an exactly linear relationship (Figure 2B). Particularly at high erosivity values, the estimates diverge to a greater degree, with the 30-minute model generally producing higher values. The linear estimate of the best-fit line between the two models is has a scaling relationship (slope) of 1.8, implying the 30-min versions are markedly higher.

3.3 Comparison with Ground-Based Data

I have compared the results from the three different IMERG-based estimates of erosivity with the ground-based observation estimates from GloREDa [Panagos et al. 2017]. Since the IMERG analyses are not applied above 60 degrees N, the intercomparison is only for the IMERG region, although GloREDa covers the entirety of the Northern Hemisphere. Maps of the ratio of erosivity estimates derived from the 30-minute IMERG data, the 3-hour IMERG data, and the MFI estimate are shown in Figure 3 (section A, B, and C respectively). Note that the values shown for the 30-minute and 3-hour data are directly

comparable to the GloREDa data (identical units), but the MFI estimate represents a different unit, and so Figure 3C is only appropriate to assess spatial patterns in the ratios, rather than absolute values.

200   Across all three IMERG methods, similar patterns emerge. There is a strong degree of agreement between GloREDa and the 30-minute and 3-hour IMERG estimates across much of Europe and Northern Asia, but much more marked differences elsewhere. In particular, GloREDa shows higher values across the Sahara, Central Asian Deserts, and the North American West. IMERG-estimates do however show clearly higher estimates in the immediate vicinity of extremely dry areas where no rainfall is recorded, in parts of the Northern Sahara and Arabian Desert. In wetter areas, differences between IMERG and

205   GloREDa also emerge; significantly greater values in erosivity from IMERG are observed in the several coastal areas, including the Western Ghats of India, the coast of Bangladesh, Myanmar, and Thailand, and the Pacific coasts of Colombia and British Columbia in Canada.

To simplify the comparison between each of the datasets, I have plotted the probability density functions of the cell values for

210   each in Figure 4. Of the IMERG-based assessments, the 30-minute estimate most closely matches that of GloREDa. Even if the MFI values are normalized by the maximum values (Supplementary Figure 1), they still do not provide a close approximation of the GloREDa values, with a much lower variability in the values. In Figure 4, both the 30-minute and 3-hour estimates both show a similar peak around the modal values as the GloREDa, but the second peak in values is somewhat lower in both IMERG-based estimates than GloREDa. The 30-minute output also shows a longer tailed distribution, with a greater

215   proportion of values at very low erosivity and some at higher erosivity than GloREDa. In essence, the 30-minute model produces more low-erosivity estimates than GloREDa, and while the most commonly-observed erosivity values (between 200-600 MJ.mm ha^{-1} h^{-1} yr^{-1}) are broadly similar to GloREDa, there is a larger degree of disagreement at higher erosivity values. I discuss the possible reasons for discrepancy in section 4, below. It is notable also that there is a large degree of difference in the cell-by-cell values even within different continents (Supplementary Figure 2), when they are compared against one another;

220   there is significant dispersion between all of the IMERG-derived estimates and the GloREDa values. The Pearson R-squared values for each are shown in Table 1, while continent-by-continent values for mean, median and standard deviation for the 30-minute IMERG data and GloREDa values are shown in Table 2.

Comparison pair	Pearson R-squared value	Slope
GloREDa – 30-minute IMERG	0.498	0.56
GloREDa – 3hr IMERG	0.633	0.34
GloREDa - MFI	0.656	0.02

Table 1: Pearson R-squared values for the comparison between GloREDa and IMERG-based estimates for erosivity.

Continent	30-min IMERG mean	30-min IMERG median	30-min IMERG Standard deviation	GloREDa mean	GloREDa median	GloREDa Standard deviation
N. America	839.2	361.9	1358.9	1676.3	744.8	2072.3
S. America	3367.1	2656.4	3138.4	5895.4	6266.3	3361.5
Europe	484.1	350.8	525.6	550.5	402.9	414.4
Asia	1313.6	153.5	2978.1	1856.7	398.6	2927.3
Africa	1231.5	708.3	1487.2	3356.8	2619.3	2977.6
Australia	659.5	215.7	1099.4	1533.9	950.7	1596.2
Oceania	4802.1	2375.7	5127.0	4100.8	2254.1	4539.9

225 Table 2: Statistics of the erosivity estimates for each continent for the GloREDa and 30-minute IMERG data. Units for all values are MJ.mm ha^{-1} h^{-1} yr^{-1}

Although there is a somewhat lower correlation in the cell-by-cell values for the 30-minute version in comparison with GloREDa than the other IMERG estimates, the 30-minute estimate nevertheless provides a closer absolute estimate to
230 GloREDa.

3.4 Monthly Estimates

The month-by-month estimates for erosivity for the year 2020 using the 30-minute data are shown in Figure 5, separated by continent. The violin plots in Figure 5A show the range of the data, as well as the mean (red bars) and median (black bars).
235 Given the large size of each continent, there is a significant degree of variability across all continents; in Europe and Australia show lower mean and median values across the year than the other continents, but across the entire dataset there is enormous variability in each month, and only limited variability is observed from month-to-month as a result of seasonal rainfall variability.

240 Since the scale of each continent is so large that interannual variability may be difficult to observe, I have subset the monthly data to areas where cropland is present. Using the cropland data of Ramankutty et al. [2008], I have selected only the cells from each continent where the cropland proportion exceeds 80% (Figure 6). Much more significant variability is observed on a month-to-month basis, with larger peaks in erosivity observed in Africa and Asia in June-July-August, in South America from January to March, and smaller peaks in erosivity in North America and Europe. Note that there is insufficient data in
245 Oceania with cropland higher than 80% to show statistics. By subsetting to areas with significant cropland, I highlight the impact of erosivity on agricultural areas and the months of the year where erosivity is of greater concern for farmers and planners across those continents.

4 Discussion

4.1 Divergence from Ground-Based Data

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It is clear that although there are some areas, particularly in Northern Europe, where the 30-minute IMERG-based estimates and those of GloREDa broadly agree, there are large areas of the world where the ratio of the two estimates remains well under 1:1. Moreover, there are a range of other areas – in particular several coastal areas, where the IMERG-based estimates are much larger than those of GloREDa. It is likely that multiple systematic effects lead to these differences, and it is informative

255 to examine the divergence between the two estimates in more detail to assess the robustness of the IMERG-derived estimates of erosivity.

While the IMERG-based estimates use the coefficients for erosivity defined by the USDA [2013] for the updated version of RUSLE, GloREDa uses the earlier coefficients. I have calculated the 3-hour erosivity estimate for both equations to test whether this would lead to major systematic differences. The difference in coefficients does not lead to large divergences, and

260 the two estimates are extremely highly correlated (Supplementary Figure 3). The updated RUSLE equation gives values that are slightly larger than the earlier equation (approximately 1.1x larger). With all else being equal, this would suggest the 30-minute IMERG data should give a value of approximately 1.1 times larger than GloREDa; however, the IMERG results are in fact systematically lower (global slope: 0.56). As such, although this might explain some of the dissimilarity between GloREDa and the 30-minute IMERG values, it does not explain the overall lower values of the IMERG estimates. Since research has

265 demonstrated that the coefficients in RUSLE version 2 better match independent observations of erosivity in contrast to the RUSLE version 1 equations [McGregor et al. 1995], I consider it a justified approach to calculate erosivity in this study.

There are large regional differences in the ratio of the 30-minute IMERG estimates and the GloREDa values. In Figure 7, I have plotted the spread of values for each continent for the two estimates, with the red line indicating the line-of-best fit, and

270 the black line indicating the 1:1 line. It is notable that continent where the values most closely fit the 1:1 line is in Europe, followed by Asia. Elsewhere, the IMERG estimates are significantly lower. The GloREDa estimates are derived from a global set of rainfall gauges, but the highest density of gauges by a significant degree is in Europe [Panagos et al. 2017]. The higher degree of agreement between the IMERG and GloREDa estimates for erosivity are found in the areas with the highest density of gauges – in other words, where the ground-based estimates have the highest degree of calibration and validation. IMERG

275 does use the Global Precipitation Climatology Center Gauges to calibrate the satellite-derived estimates [Huffman et al. 2019], which has a higher density of gauges in North and South America, Africa, and Southeast Asia, than the gauges used in the GloREDa analysis [Panagos et al. 2017]. While both IMERG and GloREDa use spatial interpolation techniques, IMERG weighs the satellite inputs more heavily in areas where gauge density is lower (like Africa and South America) whereas GloREDa does not. Given that the two estimates have better agreement in terms of absolute values where GloREDa has the

280 highest gauge density, I suggest that the disagreement elsewhere may be due to the lower amount of available data from ground-based sources, whereas the satellite data provides a globally consistent estimate, which may be more robust for calculating erosivity.

In several desert areas around the world, including the Atacama and Namib deserts, GloREDa values exceed 100 MJ.mm ha⁻¹ h⁻¹ yr⁻¹, but given in some of these areas annual rainfall is lower than 10mm, the high values in GloREDa are physically

285   implausible. While some studies have shown IMERG v06 can over-predict rainfall in the Arabian desert (Alsumaiti et al. 2020), the exclusion of storm events with less than 12.5mm of rainfall in total would also exclude the small systematic error from satellite overprediction of very low rainfall totals in desert zones from influencing erosivity estimates. This further supports the use of IMERG over sparse-gauge based estimates for erosivity. Conversely, IMERG may miss highly local peaks in orographic precipitation – one example is the island of Maui in the Hawai'ian island chain, where local maxima in rainfall

290   can exceed 5000mm of annual rainfall; however, this is not captured by the coarse IMERG data. As such, the satellite-derived estimates may be out-performed by gauge-based estimates where gauge density is very high or able to capture localised maxima.

As well as continent-by-continent differences, there are other clear zones of divergence between the IMERG and GloREDa

295   estimates. As mentioned above, these include several coastal areas in India, Southeast Asia, and the Pacific coastlines of Colombia and Canada, where the IMERG estimates exceed those of GloREDa by a significant degree [Figure 3]. These areas are all areas where both IMERG (Supplementary Figure 4) and GPCC-gauged rainfall is extremely high [Schneider et al. 2014], and the IMERG-derived erosivity estimates broadly mirror the spatial patterns observed in the annual rainfall totals. I suggest that once again the satellite data may be more sensitive to the extreme precipitation in these areas than GloREDa due

300   to the absence of gauges with suitable data for erosivity estimates in these areas.

4.2 Limitations of IMERG-based erosivity estimates

Although IMERG provides a globally consistent estimate of rainfall, limitations remain both with the rainfall data and the calculation of erosivity. Since satellite observations of intense rainfall depend upon the satellite overpasses coinciding with the

305   time of the local rainfall, it is possible that large peaks in rainfall (particularly when associated with infrequent tropical storms) may be missed by satellite rainfall products [Marc et al. 2022]. Although erosivity of rainfall does not scale in a strongly non-linear manner with rainfall intensity, these extreme storms may contribute a large proportion of overall annual rainfall in some settings [Khouakhi et al. 2017, Marc et al. 2022], so if these rainfall peaks are missed by the satellite observations, then rainfall erosivity may still be underestimated. In addition, the spatial resolution of IMERG data is large (0.1 decimal degrees), and so

310   observations of local variability in rainfall totals as a result of orographic boundaries or other microclimatic differences will be limited by resolution. However, agricultural zones with relatively low topographic variability are more likely to be represented fairly, and these zones may be more critical for the socio-economic impacts of soil degradation by rainfall erosion. I have compared the 30-minute IMERG-derived erosivity estimates with the ground-based estimates from GloREDa and plotted the ratio of the two estimates in comparison with the maximum topographic slope calculated in each grid cell

315   (Supplementary Figure 5). The maximum slope is calculated from the NASA SRTM data [Farr et al. 2007]. There is not a

As noted above, there are limitations with the simplifications used to generate the MFI and 3-hour erosivity estimates. The
MFI value is only appropriately applied to climatically homogenous zones, which suggests a global MFI value is unlikely to

320 be appropriate; moreover, the conversion from MFI to R-factor is neither consistent nor agreed upon in the published literature.
Despite the lower computational requirements to calculate MFI, I suggest that the limitations associated with it mean that the
30-minute version should be considered superior and used wherever data and computational capacity is available. While there
is a good degree of agreement between the 3-hour estimate and GloREDa, prior research has shown that the 3-hour
simplification of TRMM-era satellite rainfall data may reduce the accuracy of the results [Vrieling et al. 2010], and the 30-

325 minute data is the only data source that can provide the appropriate temporal resolution [Bezak et al. 2022].

Other satellite-derived rainfall products are available, including GSMaP [Kubota et al. 2007, 2020] and the hybrid MSWEP
[Beck et al. 2017], but since GSMaP is available only at a 1hr temporal resolution and MSWEP at 3hr maximum temporal
resolution, neither of these products are appropriate to calculate rainfall erosivity. Bezak and coauthors [2022] have used
CMORPH to calculate rainfall erosivity globally, since it is available at 30-minute temporal resolution. Both IMERG and

330 CMORPH use passive microwave observations which is spatially propagated before infra-red precipitation observations are
incorporated. Both algorithms use a variety of methods to interpolate observations, and in fact IMERG uses the CMORPH
Kalman filter Lagrangian time interpolation scheme [Joyce et al. 2004, 2011]. The two products perform comparably when
compared with observations [Alsumaiti et al. 2020, Llauca et al. 2021, Mekonnen et al. 2021, Montes et al. 2021, Nwachukwu
et al. 2020], although several studies have suggested the version 6 of IMERG is performs better than CMORPH across a

335 diverse set of climatological regimes [Llauca et al. 2021, Mekonnen et al. 2021, Montes et al. 2021, Tang et al. 2020]. It is not
my intention in this study to adjudicate which of the two satellite products performs better, but instead to demonstrate the use
of IMERG data to estimate erosivity in the same manner as Bezak and coauthors [2022] did with CMORPH.

4.3 Erosivity in Arable Zones

340 The implications of these erosivity estimates for geomorphological processes vary depending on the location. In steep,
mountainous regions, the dominant process of erosion is bedrock landsliding [e.g., Hovius et al. 1997, Marc et al. 2019], while
the impact of overland flow and rain-splash on erosion of surficial materials contributes a smaller proportion of overall
erosional fluxes. RUSLE-based approaches do not consider bedrock landsliding, and as a result these erosivity estimates are
not as relevant in steep, upland areas. The extremely high erosivity values observed in, for example, Papua New Guinea and

345 the Eastern Himalayan Syntaxis may therefore not be directly correlated with overall erosional fluxes from these regions where
bedrock landsliding is more dominant [Hovius and Stark, 2006].

Soil loss by purely rain-driven processes is highly relevant in areas of agricultural cultivation, in part due to broadly lower
topographic steepness but also because of the potential impact of soil degradation on agricultural productivity. As such, I have

350 compared the 30-minute IMERG erosivity estimates with datasets on the location of cropland and pastures around the world [Ramankutty et al. 2008] to assess whether highly agriculturally productive areas experience high erosivity values, or not.

At low crop densities, there is a somewhat higher variability in erosivity values than at higher crop densities (Figure 8). This is especially pronounced in Asia and North America. At higher crop densities, erosivity values are more consistent. The mean value of erosivity remains relatively consistent across all crop densities, with the exception of Europe where at moderate-to-

355 high crop density, erosivity declines. This suggests that the location of cropland is subject to lower rainfall erosivity in Europe, but not elsewhere. Ramankutty et al. [2008] also generated estimates of pastureland, which is also a critical area for soil loss as a result of erosion. I have compared pasture area with the 30-minute IMERG estimate of erosivity (Supplementary Figure 6). Unlike cropland, in both North America and Asia as the proportion of pastureland increases, the erosivity decreases. This suggests that pastureland may be less vulnerable to highly erosive rainfall than cropland across these two continents. Although

360 these are very spatially coarse assessments, by cross-comparing where highly erosive rain falls with agricultural zones it is possible to highlight areas of concern for soil degradation. However, it is also critical to note that soil erosion is not entirely dependent on rainfall erosivity, and to fully contrast areas of concern for erosion and agricultural areas, further research will need to incorporate the other parameters in the RUSLE equation including topography, land cover, and land management practices.

365 While the probability density function of the 30-minute IMERG erosivity and GloREDa erosivity estimates (Figure 4) show a broadly similar 2-peak distribution (albeit with the higher erosivity peak somewhat in the GloREDa estimates offset to higher values), when I limit the data to only the areas with cropland greater than 80% (Supplementary Figure 7) or pasture greater than 80% (Supplementary Figure 8), there is a significantly larger proportion of values in the GloREDa estimates at higher erosivity values. For areas with 80% or more cropland, the lower peak in erosivity values overlaps for the IMERG and

370 GloREDa data (although mean values are higher for GloREDa, and the modal value is found in the second peak, rather than the first as in the IMERG results), but for areas with 80% or more pastureland, the entire density function of GloREDa results is significantly higher than that of the IMERG-derived erosivity. This comparison shows that the satellite estimates of erosivity suggest that global cropland and pasture areas are subject to lower rainfall erosivity than the ground-based estimates previously indicated.

375

5 Conclusions

In this study, I have used the IMERG satellite-derived precipitation product to generate a global estimate of rainfall erosivity. I have tested three methods, including two simplifications of high-temporal frequency data, and while these do produce similar global patterns of erosivity to the 30-minute data I suggest that the estimate derived from the 30-minute data is the most

380 appropriate global model, not only because it provides a closer approximation of ground-based values in areas where the density of ground-based gauges used by GloREDa [Panagos et al. 2017] is greatest, but also since it allows for the equations used in the standard formulation of the widely-used RUSLE equation to be fully applied without simplification. A further

benefit of this approach is that it allows for rapid calculation of monthly erosivity estimates, allowing researchers and practitioners to assess the peaks and troughs in erosivity across each year, rather than a single static value.

385 When contrasted with ground-based estimates, the IMERG-derived erosivity estimates are more similar in Europe, where the density of gauges used to calculate the ground-based estimate is higher, but in many other areas – and in particular areas of high cropland and pasture density – the IMERG estimates show lower erosivity values. Further research is necessary to ground-truth the IMERG-based estimates of erosivity in these data-poor areas, to test whether satellite-derived erosivity can be used in place of gauges, and thus maximising the use this globally-consistent dataset for erosivity.

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Code and Data availability

The IMERG data were provided by the NASA/Goddard Space Flight Center's GPM Team and PPS, which develop and compute IMERG version 06B as a contribution to the Global Precipitation Monitoring mission, and archived at the NASA GES DISC. All methods necessary to replicate these results can be found in the text. Datasets on global crop production and

395 yield are available at http://www.earthstat.org/, accessed November 2nd, 2022. The 20-year estimates of erosivity derived from IMERG are available in the supplementary material. All monthly data for erosivity will be released through the NASA GES DISC and code through the NASA Github upon completion of the NASA data release process, and are available upon request from the author until that date.

400 **Author Contribution**

R.E. Conceptualized the study, conducted data analysis, and wrote the manuscript.

Competing Interests

The author declares that he has no conflict of interest.

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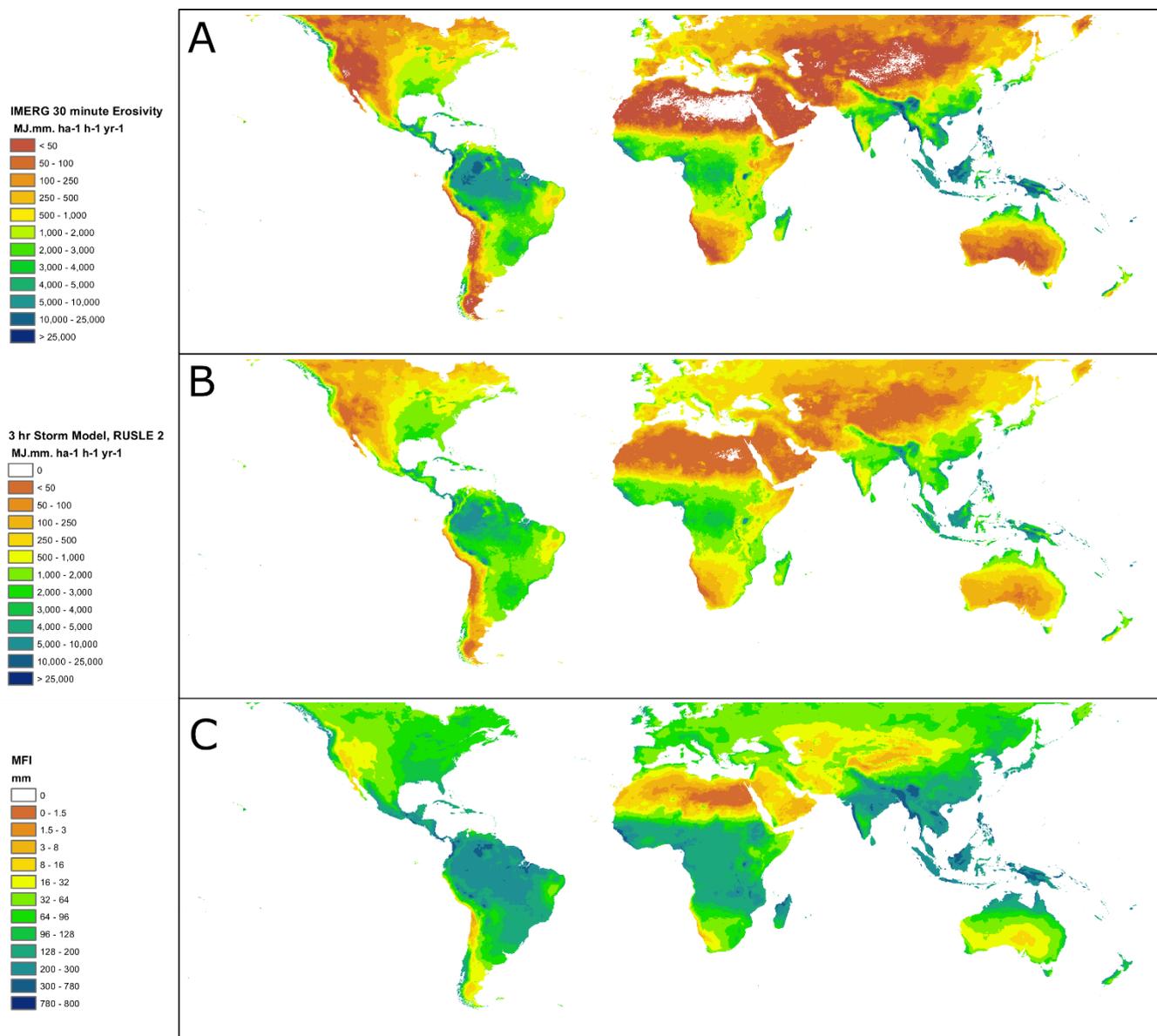
Figure 1: Global map of erosivity estimates derived from the three different approaches. (A) erosivity calculated using 30-minute IMERG data. (B) erosivity calculated using the 3-hour IMERG data and storm simplification. (C) Modified Fournier Index of erosivity. Note that the colour scheme for (A) and (B) are the same, while the MFI colour scheme has been selected to highlight the similarity in spatial patterns, rather than absolute values with the other two estimates.

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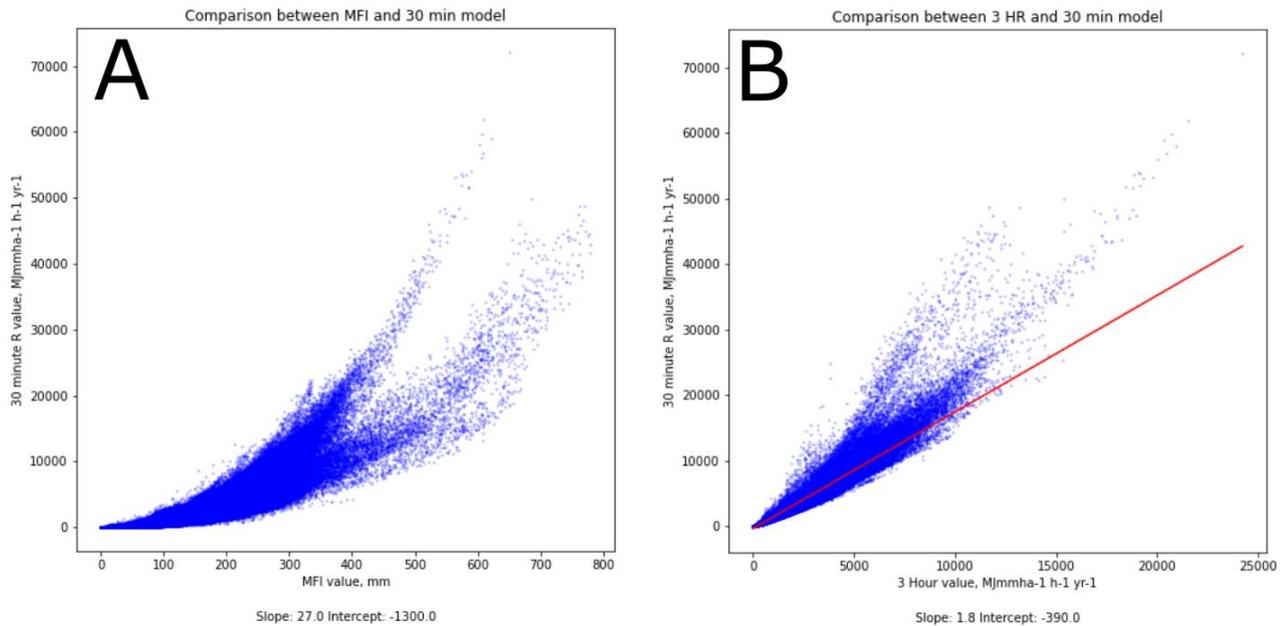
Figure 2: Comparison between cell-by-cell values of the 30-minute IMERG estimate of erosivity (y-axis) and the two other methods; (A) shows comparison between 30-minute IMERG estimate and MFI, while (B) shows the comparison between 30-minute IMERG estimate and the 3-hour IMERG data estimate. Note that the red line in (B) shows the 1:1 line, with values above that line indicating higher erosivity estimates in the 30-minute version.

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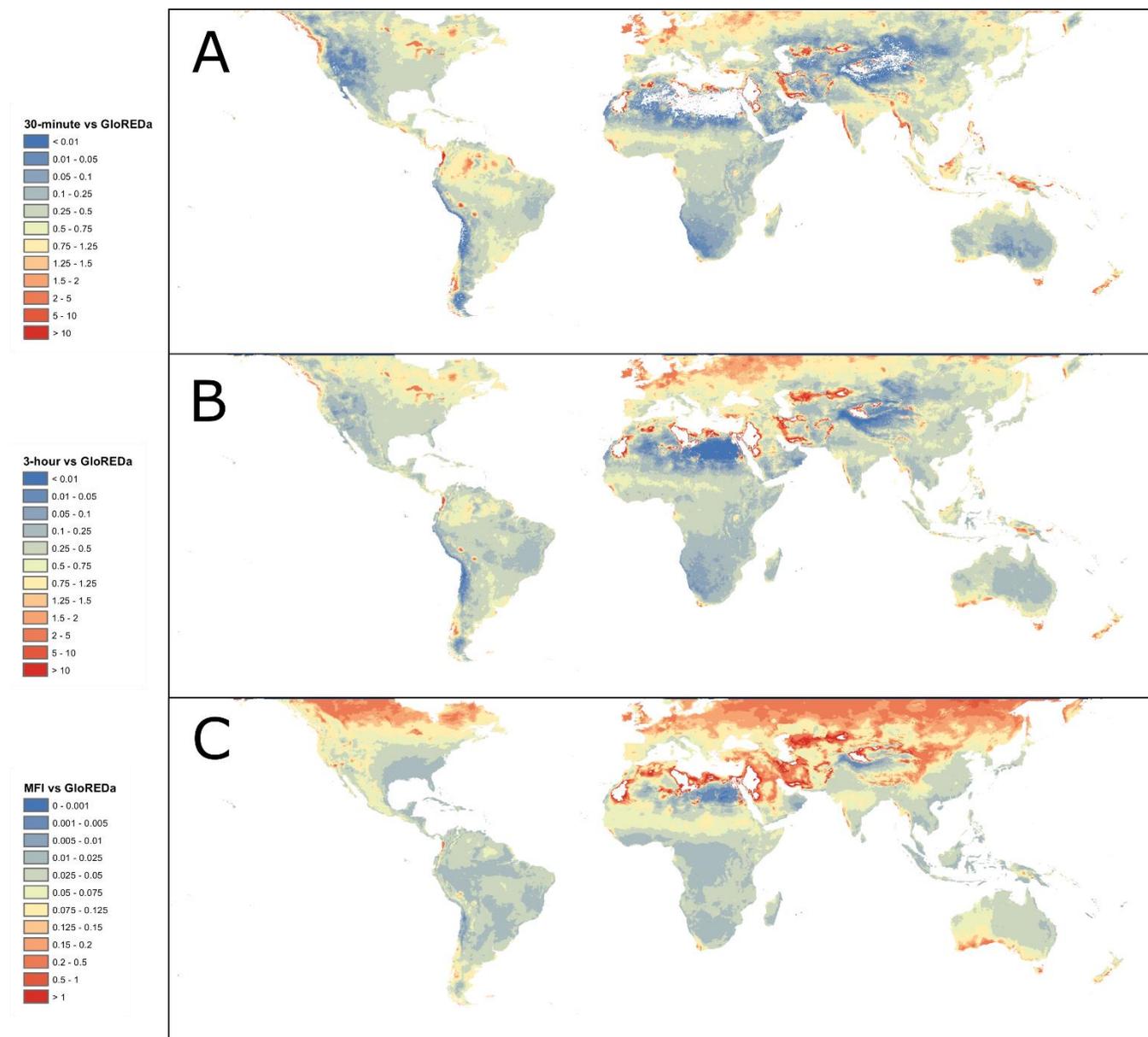


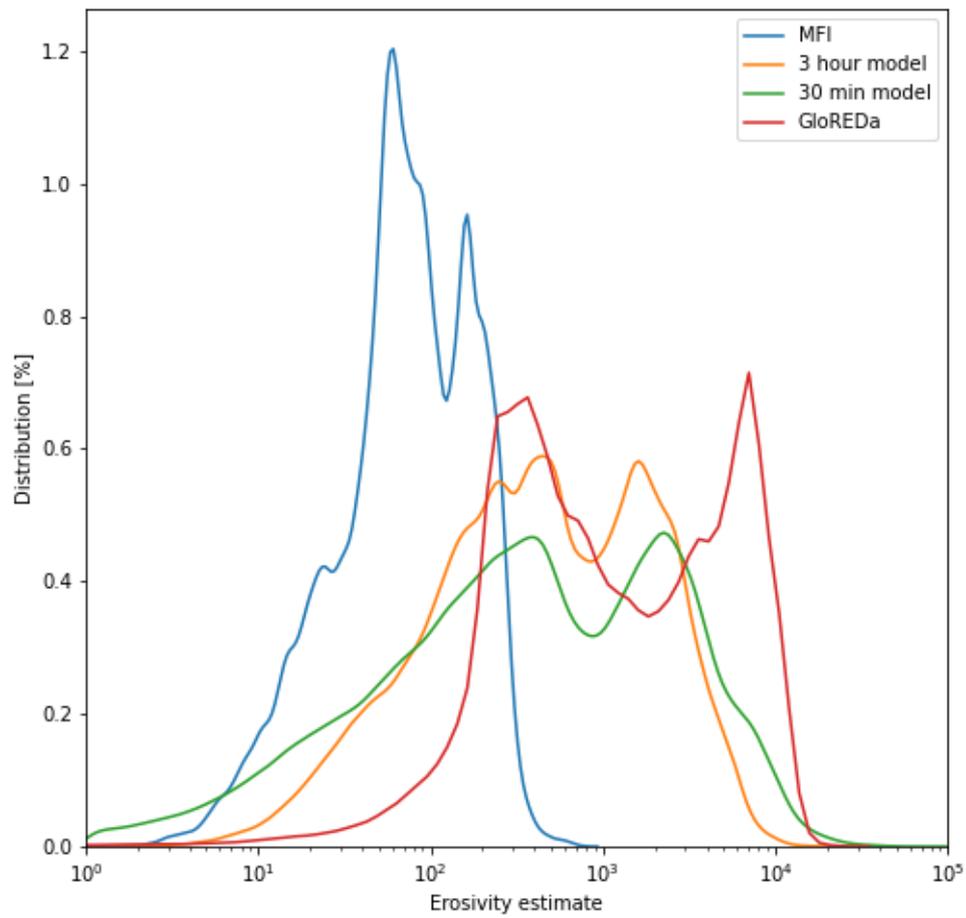
Figure 3: Global maps of the ratio between the IMERG-derived estimates of erosivity and the ground-based gauge estimates from GloREDa [Panagos et al. 2017]. The three panels show the comparison between GloREDa and (A) erosivity calculated using 30-minute IMERG data. (B) erosivity calculated using the 3-hour IMERG data and storm simplification. (C) Modified Fournier Index of erosivity. Note that the scale for (A) and (B) are identical, since they have the same units; however, the values in C are lower since the MFI has not been scaled to the other values. The scale is thus lowered to allow for comparison of spatial patterns with (A) and (B).

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Figure 4: Probability density function for the cell-by-cell values for each of the IMERG erosivity estimates and the GloREDa estimate.
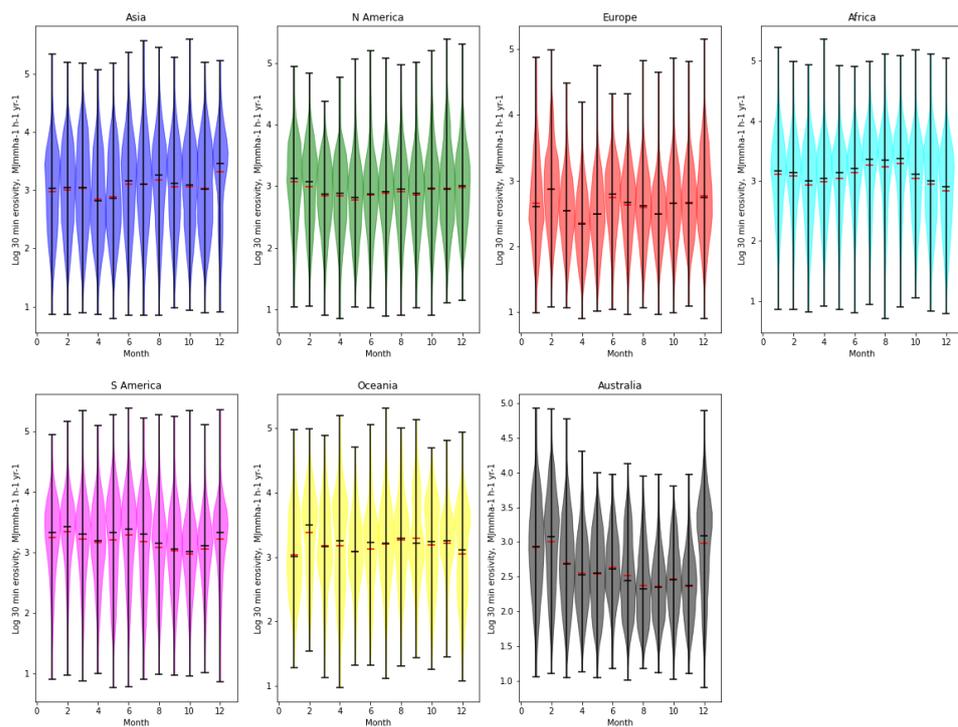
Figure 5: Monthly variability in erosivity calculated using IMERG 30-minute data, for each continent for the year 2021.

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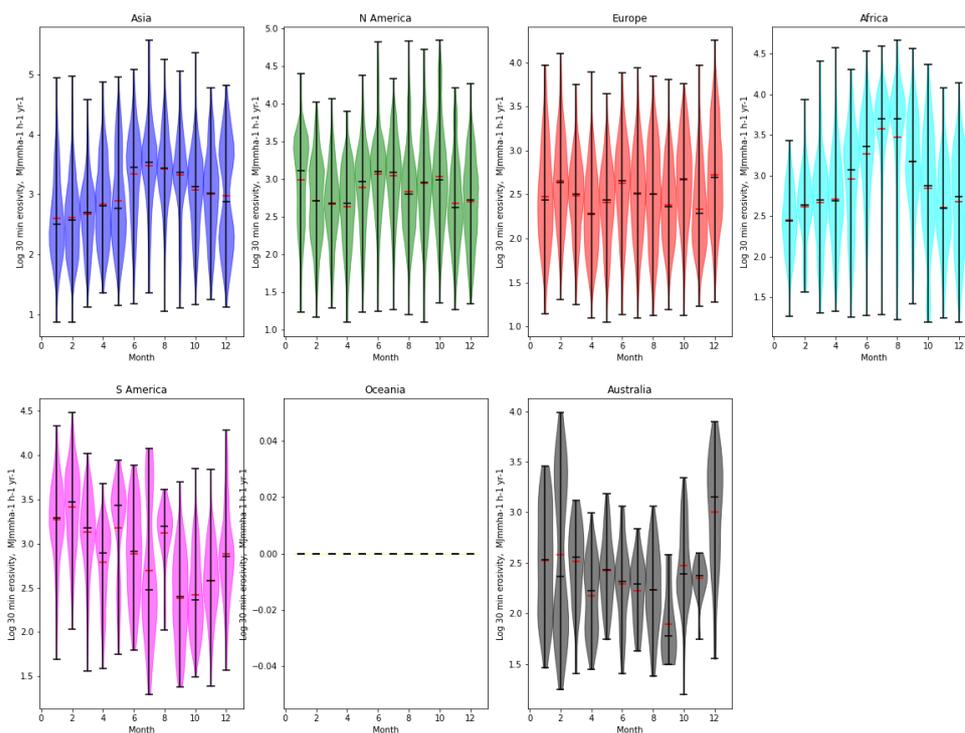


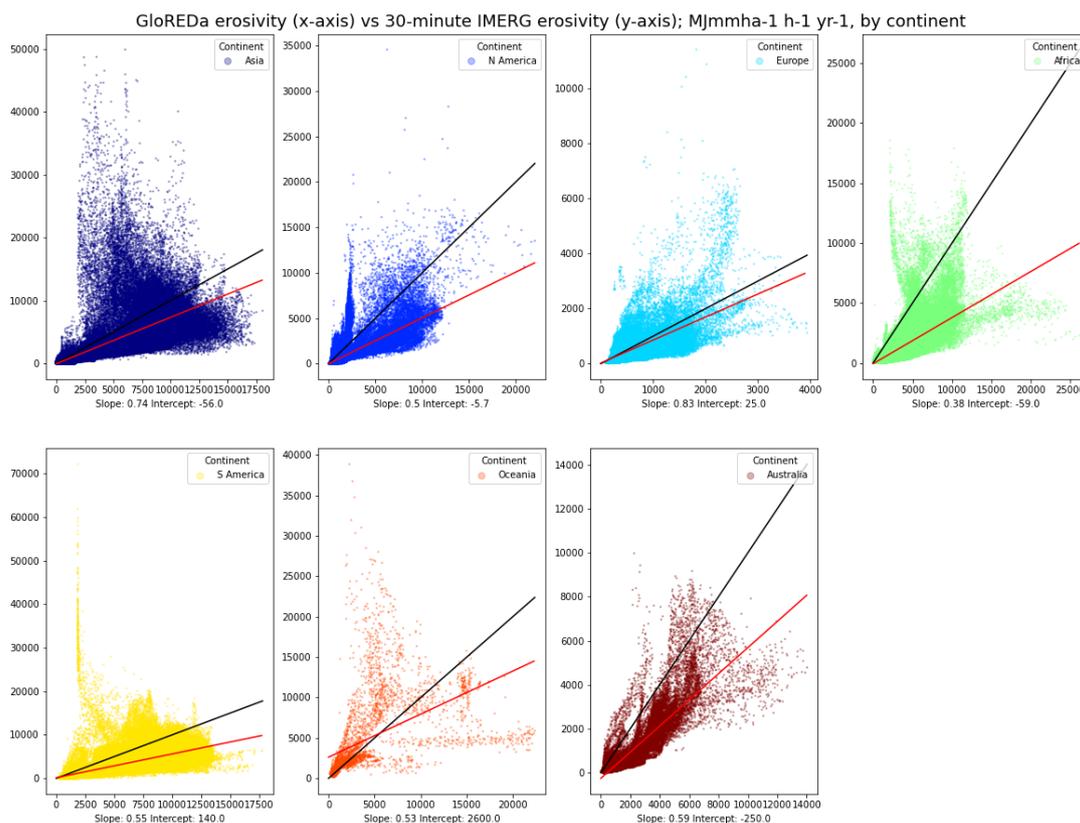
Figure 6: Monthly variability in erosivity calculated using IMERG 30-minute data, for each continent for the year 2021. In this figure, only grid cells where the proportion of cropland exceeds 80% are shown.

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Figure 7: Comparison of cell-by-cell values for GloREDa (x-axis) and the 30-minute IMERG-derived erosivity estimate (y-axis) for each continent. The black line in each figure shows the 1:1 relationship, while the red line is the linear regression estimate of the best fit line for the data. Below each figure, the slope and intercept of the best-fit line are shown. All values have units of MJ.mm ha^{-1} h^{-1} yr^{-1}.

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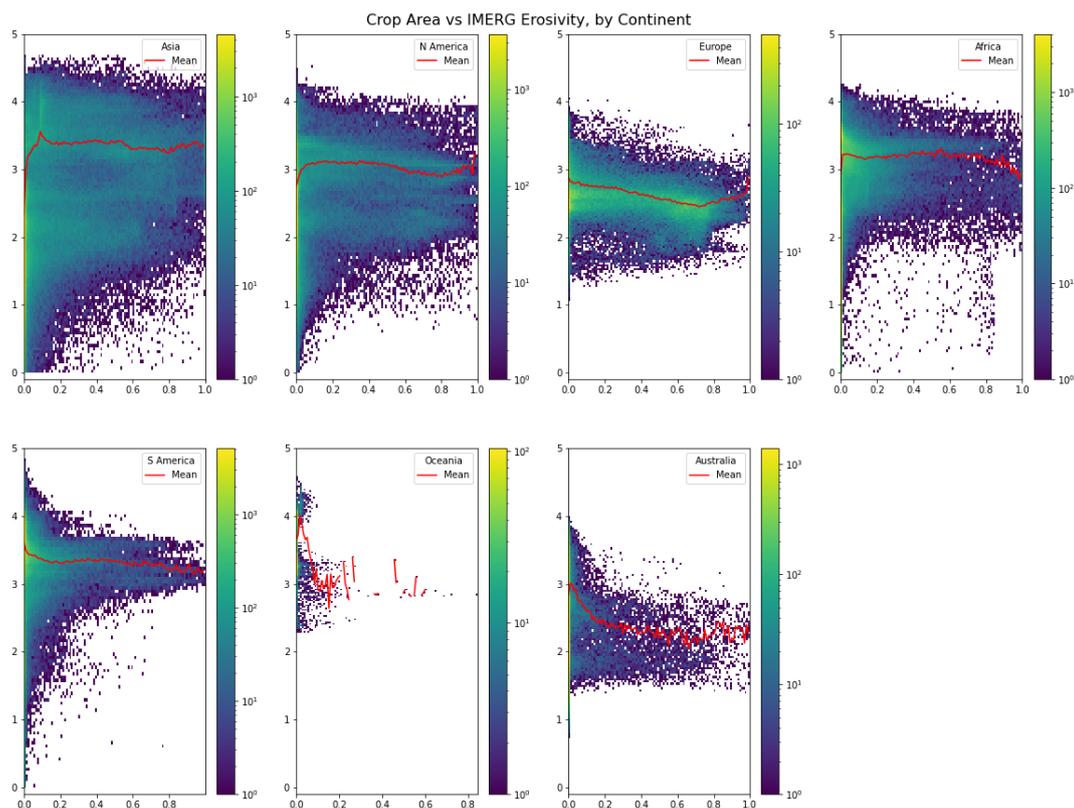
Figure 8: 2-dimensional histogram of the cell-by-cell values of the 30-minute IMERG estimate (y-axis, note logarithmic scale) and the fraction of cropland in that cell [Ramankutty et al. 2008]. The colour scale indicates the number of cells with those values. The figure shows the values distributed across each continent; continent labels are shown in the legend. The red line in each figure indicates the moving mean for different crop fractions.