Use of A High-Resolution-Satellite-Based Precipitation Product in Mapping Continental-Scale Rainfall Erosivity: A Case Study of the United States

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Abstract

A rainfall erosivity map is useful for understanding the spatial variability of rainfall erosivity, and for identifying regions vulnerable to soil erosion by rainfall. This study addresses a new approach to mapping rainfall erosivity on a continental scale, based on a high-resolution-satellite-based precipitation product—the National Oceanic and Atmospheric and Atmospheric Administration's Climate Precipitation Center morphing technique (CMORPH). For this purpose, a rainfall erosivity map of the contiguous United States is experimentally developed, and is analyzed from the perspectives of the corresponding hydrological basins and climate features. In general, we conclude that the CMORPH precipitation product is useful for mapping rainfall erosivity on a continental scale. In the contiguous United States, the mean of rainfall erosivity was 1,260 MJ mm ha^{-1} h^{-1} yr^{-1}, with high variability by region. The coastal regions showed the highest rainfall erosivity, at 20%. The seasonality of the rainfall erosivity was evident in most coastal regions (rainfall erosivity depends on climates). The rainfall erosivity in the tropical climate zone was the highest, whereas it was the lowest in the arid climate zone (and spatially homogeneous). However, corrections were required for improving the accuracy of the CMORPH precipitation in most coastal regions, i.e., to secure a better rainfall erosivity product. Compared to a rain gauge-based rainfall erosivity map, the CMORPH's rainfall erosivity map tended to underestimate the rainfall erosivity in coastal regions near the Gulf of Mexico and Atlantic Ocean, but overestimated it in coastal regions near the Pacific Ocean.

Keywords: Soil erosion; Rainfall erosivity; R-factor; High resolution satellite-based precipitation; CMORPH

1. Introduction

The identification of regions vulnerable to soil erosion is very important, as soil loss has a significant influence on reductions in agricultural land, reservoir capacity, water quality, and carbon sequestration (Conner et al., 1989; Smith et al., 2001; Lal, 2005; Panagos et al., 2016a; 2016b). Typically, soil erosion (e.g., interrill erosion) is caused by two physical processes (Nearing et al., 1994): a soil particle separation process owing to the impact of the rainfall kinetic energy on the soil surface, and a sediment transportation process owing to surface flows. The erosion depends on the rainfall features in the region (e.g., intensity and terminal velocity), as well as the topographical and pedological features (e.g., slope, soil type, and vegetative cover) (Jayawardena and Rezaur, 2000). The rainfall intensity and its kinetic energy on the soil surface are the primary factors causing interrill erosion, as these factors lead to the physical separation of soil particles. In the hydrologic community, the rainfall erosion index (a R-factor based on the two factors) has been used to quantitatively represent and measure degrees of soil erosion from rainfall (Goovaerts, 1999; Panagos et al., 2016a). The universal soil loss equation (USLE, Wischmeier and Smith, 1978) and revised USLE (Renard et al., 1991) are good examples of calculations that employ the R-factor as a major parameter in estimating soil loss. However, it is challenging to map rainfall erosivity using ground-based rain-gauge observations (hereinafter referred to rain-gauge data), as they cannot represent the spatial distribution of the precipitation. As such, they require interpolation to map the rainfall erosivity. Accordingly, high-resolution-satellite-based precipitation products might be an alternative to mapping rainfall erosivity on a large scale.

The R-factor has been estimated using various methods dependent on various temporal resolutions of precipitation data: sub-hourly (Wischmeier and Smith, 1978; Yin et al., 2007), hourly (Ramos and Durán, 2014), daily (Angulo-Martínez and Beguería, 2009), monthly (Renard and Freimund, 1994; Hernando and Romana, 2015), and yearly (Lee and Heo, 2011) data. The point-scale R-factor estimated from these methods has been mapped using an interpolation approach, allowing researchers to estimate amounts of potential rainfall erosivity in ungauged areas, understand the spatial variability, and identify regions vulnerable to soil erosion. As a result, over the last four decades, rainfall erosivity maps have been presented on various scales: continental-scale maps (Roose, 1977; Oduro-Afriyie, 1998; Panagos et al., 2015), national-scale maps (Elwell and Stocking, 1976; Krauer, 1988; Lenvain et al., 1988; Oduro-Afriyie, 1996; Mikhailova et al., 1997; Da Silva, 2004; Leow et al., 2011; Klik et al., 2015; Panagos et al., 2016a), and regional-scale maps (Angulo-Martinez and Beguería, 2009; Ufoegbune et al., 2011; Elbasit et al., 2013; Ramos and Durán, 2014). Panagos et al. (2017) developed a novel global R-factor map for representing high spatial variability in rainfall erosivity for six continents, using rain-gauge data collected from 63 countries.

The first rainfall erosivity map in the United States was introduced in an agriculture handbook (Wischmeier and Smith, 1965). The map was developed from 22 years of rainfall records, and 11 of the western states were omitted from the map, as sufficient long-term recording-rain-gauge records were unavailable. In 1997, the United States Department of Agriculture revised the map, using rainfall records from 1,082 stations over 20 years (Renard et al., 1997). The rainfall erosivity map was divided into five regions: Eastern and Western United States, California, Oregon, and Washington, and Hawaii. Since then, only a few studies have developed soil erosivity maps for the United States (Niedermeier, 1998; Wang et al., 2002; Cooper, 2011).

Using rain-gauge data to estimate the R-factor is the easiest way to secure and handle data. However, many studies addressed the limitations in employing rain-gauge data compared to remote sensing data, such as the advantages of satellite-based precipitation products in being able to capture the spatial distribution of precipitation regardless of the type of terrain, and the ability to track a storm from the ocean to an inland area (Buytaert et al., 2006; Nesbitt and Anders, 2009; Anagnostou et al., 2010; Kim and Yoo, 2014; Kim et al., 2015). Technically, the rain-gauge data can only represent a measured value within a constrained radius of observation instruments, as it is a point-scale. In addition, it is affected by the sampling density of rain-gauge data, which can vary with different terrain types. Thus, the greatest uncertainty in the rainfall erosivity map constructed from rain-gauge data is probably related to the transition areas between different topographic conditions, climate zones, and ungauged areas (Panagos et al., 2017).

Most studies using rain-gauge data have employed a spatial interpolation method for predicting and mapping rainfall erosivity in the transition areas, e.g., inverse distance weighting, radial basis functions, regression, kriging, and co-kriging methods (Goovaerts, 1999; LOWLAND, 2005; Bonilla and Vidal, 2011; Khorsandi et al., 2012; Meusburger et al., 2012; Lee and Lin, 2015; Meddi et al., 2016). Thus, there is a high possibility that the interpolated rainfall erosivity values will have a large amount of uncertainty, arising from the use of an interpolation method (Goovaerts, 1999; Panagos et al., 2015; Ballabio et al., 2017). Vrieling et al. (2010) and Zhu et al. (2011), understood the usefulness of remote sensing data, and utilized 3-hourly satellite-based precipitation data (e.g., tropical rainfall measuring mission products, (TRMM)) to map rainfall erosivity. Vrieling et al. (2010) concluded that the 3-hourly and 0.25° (approximately 27 km temporal resolution) resolutions of the TRMM data provided insufficient details for representing high-intensity erosive events. Zhu et al. (2011) indicated that the 3-hourly temporal resolution was not sufficiently fine to map rainfall erosivity, and recommended a sub-hourly temporal resolution for mapping. These conclusions have consistently provided support for employing high-resolution-satellite-based precipitation products with a sub-hourly temporal resolution to estimate and map rainfall erosivity on a continental scale.

This study aims to propose a new approach for estimating and mapping a rainfall erosivity index, the R-factor, on a continental scale. The approach employs a high-resolution-satellite-based precipitation product, i.e., the National Oceanic and Atmospheric Administration (NOAA) Climate Precipitation Center morphing technique precipitation product (hereinafter referred to CMORPH). In addition, the approach employs a standard method that requires precipitation data in a 30-min temporal resolution. As a case study, the approach is applied to the contiguous United States (CONUS). The rainfall erosivity map over the CONUS is analyzed to identify and understand the rainfall erosivity attributes from various points of view: annual, monthly, hydrologic unit basins, and climate zones.

2. Materials and Methods

2.1 Study Area

The CONUS is chosen as the application domain because it has a variety of geographic and climate features. The CONUS consists of the 48 states of the US (excluding Alaska, Hawaii, and the Caribbean) and eighteen river basins, based on the United States Geological Survey hydrologic unit codes. These basins include either the drainage area of a major river, or the combined drainage areas of a series of rivers (Seaber et al. 1987, Ahn, K. H., Palmer). The climate features of the CONUS vary owing to the impacts of oceans (e.g., the Pacific Ocean, Gulf of Mexico, and Atlantic Ocean) and geographic features, including mountains and arid/semi-arid desserts. It consists of 15 climate zones such as tropical, arid, temperate, and cold. Generally, the climate of the CONUS becomes warm and dry in the west and south regions, and humid in the east and north regions.

The annual precipitation over the CONUS is approximately 760 mm, and varies with regional topography and climate characteristics. For example, for western regions with warm and dry climatic features, the average annual precipitation is approximately 630 mm, whereas it is approximately 1,250 mm for southeastern regions. In addition, the average annual precipitation in the central regions unaffected by oceans is approximately 420 mm, which is relatively lower than the other regions.

Unlike the central regions, precipitation in the western and southeastern regions is affected by the oceans. In the western region, extratropical cyclones or jet streams (usually from the Pacific Ocean between September and May) cause a large amount of rainfall (https://www.wpc.ncep.noaa.gov/research/mcs_web_test_test_files/Page1539.htm). Moreover, atmospheric rivers cause heavy rainfall during the rainy season (Ralph et al., 2006; Han et al., 2019). The southeastern regions have higher amounts of precipitation than the other regions, mainly owing to the humid air coming from the Atlantic and Caribbean Oceans and the Gulf of Mexico. Between late summer and early fall, tropical cyclones move from the Atlantic Ocean and Gulf of Mexico to the southeastern regions, providing a quarter of the annual precipitation (Knight and Davis, 2007).

2.2 CMORPH Precipitation Product

The CMORPH is a very high spatial and temporal resolution global precipitation product that covers over the CONUS, with a history longer than ground-based remote sensing data such as weather radars. The CMORPH produces global precipitation estimates at an 8 km × 8 km resolution every 30 min. Overall, this technique exclusively uses precipitation estimates derived from low Earth orbit (LEO) satellite-derived passive microwave (PWM) observations. As the coverage of the PMW-based retrievals is severely limited in the half-hour window owing to the spatial and temporal sampling natures of LEO satellites (even when multiple satellites are used), the CMORPH takes advantage of the high temporal resolution of the geostationary satellite infrared (IR) imagery to create motion vectors for the cloud systems. It subsequently applies the cloud motion vectors to the available PMW-based retrievals to produce continuous precipitation estimates over the entire globe. At each half-hour window, the availability of the IR data is almost guaranteed at a given location, and can be used to extract the spatial propagation of precipitation features. For additional details regarding the CMORPH technique, interested readers are referred to Joyce et al. (2004), Xie et al. (2017) and Chen et al. (2020).

The entire CMORPH dataset in version 1.0 is reprocessed and extended to cover the period from 1998 to the present. The reprocessing includes a bias correction using gauge data (Xie et al. 2017). There are three types of precipitation estimates from the CMORPH: 30-min/8 km, 3-h/0.25°, and 1-day/0.25°. As the CMORPH provides precipitation data over 30 min in mm/h, to obtain hourly precipitation estimates for calculating the R-factor, each half-hourly rainfall rate estimate is assumed to be constant for the entire half hour (e.g., a 1.0 mm/h rainfall rate estimate over 30 min = 0.5 mm of accumulated precipitation during that time). Each 30-min estimate is accumulated to obtain the hourly precipitation.

This study is conducted with the understanding that the accuracy of the CMORPH might be lower than that of rain-gauge data in some regions, and briefly compares the CMORPH precipitation data with the rain-gauge data in the discussion part.

2.3 Rainfall Erosivity Index: R-factor

The R-factor has been denoted by various expressions: rainfall erosivity, rainfall erosivity index, rainfall erosivity factor, rainfall erosion factor, rainfall erosion index, rainfall-runoff erosivity, rainfall erosive index, R-value, and energy-intensity. In all of these expressions, the R-factor is defined as a multiplication of the rainfall kinetic energy and rainfall intensity, based on long-term data (Wischmeier and Smith, 1958). The R-factor uses MJ mm ha^{-1} h^{-1} yr^{-1} as the SI unit; it represents the degree of soil erosivity from rainfall.

A number of methods for estimating the R-factor have been developed, depending on the temporal resolution of the precipitation data. These include the standard method (Wischmeier and Smith, 1978; Renard et al., 1997), simple methods (Lee and Heo, 2011), and alternative index methods (Fournier, 1960; Arnoldus, 1977). The simple and alternative index methods mainly use a rainfall parameter-based regression equation to estimate the R-factor (Meddi et al., 2016). The alternative index methods include the "KE index" method (Hudson, 1971) based on rainfall kinetic energy (E) and erodibility (K), AI_m index method (Lal, 1976) based on rainfall amount (A) and maximum rainfall intensity (I_m), and the climatic coefficient index (Fournier, 1956). The standard method has been widely used to estimate the R-factor, as the resultant R-factor is regarded as the finest value (Lombardi Neto and Moldenhauer, 1992; Bertol et al., 2007; Meusburger et al., 2012; Panagos et al., 2016b). The standard method uses all erosive storm events, as quantified by the rainfall kinetic energy and maximum rainfall intensity over 30 min (Stocking and Elwell, 1973; Hoyos et al., 2005; Oliveira et al., 2013). The R-factors from other methods (using coarser temporal resolutions) have been compared with the results from the standard method to verify their performance. As the temporal resolution of the CMORPH is fine and sufficient for application in the standard method, this study adapts the standard method to estimate the R-factor.

Figure 1

Fig. 1 presents a diagram of the methodology, and consists of steps for mapping rainfall erosivity and representing the details of the classification process for an independent storm event. First, the domain fitting is trimmed to the CONUS, as the CMORPH comprises global-scale precipitation data. A threshold is applied to eliminate small amounts of rainfall arising from rainfall intermittency; this is a pre-processing step for clarifying the inter-event time definition for classification of independent rainfall pulses. The independent rainfall pulses are then classified, considering the conditions as shown in blue-line box in Fig. 1. The box illustrates the details of the classification of independent rainfall pulses. This is an important process, as it accounts for a number of effective rainfall events for estimating rainfall erosivity at each grid of the CMORPH data. Subsequently, the maximum intensity of each rainfall pulse in 30 min is extracted. The R-factor is then estimated, based on the following equation (Wischmeier and Smith, 1978; Brown and Foster, 1987; Panagos et al., 2015):

$$\mathrm{R} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m_i}(EI_{30})_j \qquad (1)$$

Where, R indicates the R-factor, in MJ mm ha^{-1} h^{-1} yr^{-1}; n is the number of years used to estimate the R-factor; *mi* is the number of erosivity events in a given year *i*, and *E* and I_{30} indicate the rainfall kinetic energy and maximum rainfall intensity in 30 min at an event *j*, respectively. EI_{30} (MJ mm ha^{-1} h^{-1}) determines the R-factor of a single event, and is defined as follows:

$$\mathrm{EI}_{30} = \left(\sum_{k=1}^{m} e_k p_k\right) I_{30} \quad (2)$$

Where, e_k is the unit rainfall energy (MJ ha^{-1} mm^{-1}), and p_k is the *k-th* rainfall volume (mm) of a storm event including m parts. k is the time period of each rainfall, and m is the duration of the storm event.

The unit rainfall energy is estimated using a rainfall intensity-energy equation derived from Van Dijk et al. (2002). The equation was verified in a number of previous studies (Marques et al., 2007; Vrieling et al., 2010). The rainfall intensity-energy equation used in this study is as follows:

$$\mathrm{e}_k = 28.3[1 - 0.52\exp(-0.042I)] \quad (3)$$

Where, I is the rainfall intensity (mm hr^{-1}). As the R-factor is estimated based on each grid, the final R-factor map is visualized with colors representing corresponding values.

3. Results

3.1 Annual and Monthly Rainfall Erosivity Maps over the CONUS

The annual R-factors from 1998–2015 were estimated using the CMORPH precipitation product and standard method. Fig. 2 shows the number of identified storm events, annual precipitation, and R-factors for each year. Overall, the results demonstrate that the trends of the annual precipitation and number of storms are similar to the increasing and decreasing patterns of the annual R-factor. In 1998, 2004, 2009, and 2015, i.e., where the R-factor was higher than other years, the number of storm events and annual precipitation were also higher than in the other years. The mean annual number of storms ranges from 25 to 30, the mean value of annual precipitation ranges from 570 to 770 mm, and the mean annual R-factor ranges from 920 to 1420 MJ mm ha^{-1} h^{-1} yr^{-1}.

Figure 2

Fig. 3 shows the rainfall erosivity map for the United States, and a probability density function of the R-factors. The rainfall erosivity map was presented at an 8 km × 8 km spatial resolution. The mean of the rainfall erosivity is 1,260 MJ mm ha^{-1} h^{-1} yr^{-1} with high variability, as expressed by the standard deviation of 1,037 MJ mm ha^{-1} h^{-1} yr^{-1}. The median (50th percentile) of the R-factor is 1,100 MJ mm ha^{-1} h^{-1} yr^{-1}. The bottom 20% of the R-factors are lower than 357 MJ mm ha^{-1} h^{-1} yr^{-1}, and the highest 20% (80th percentile) are greater than 2,200 MJ mm ha^{-1} h^{-1} yr^{-1} (see Fig. 3b).

Figure 3

The range of the R-factor is from 33 to 6,000 MJ mm ha^{-1} h^{-1} yr^{-1}, and it varies considerably with region. As expected, the results indicate that the high values of the R-factor are estimated mainly around the coastal regions. The highest 20% (of the R-factor) is estimated from the coastal regions of the Pacific Ocean, Gulf of Mexico, Florida Peninsula, and Atlantic Ocean. Among the coastal regions, for example, the western north region (in contact with the North Pacific Ocean) is vulnerable to soil erosion by rainfall, as this region has seasonal and extreme rainfall storms (e.g., atmospheric rivers) routinely inflowing into the regions during winter. Moreover, high rainfall intensity is commonly observed, owing to complex terrain (Han et al., 2019). Along the same lines, the spatial patterns of rainfall erosivity in a chain of mountains in the western/north United States were completely different between the western (complex terrain) and eastern (flat terrain) regions.

The map demonstrates that the inland and coastal regions affected by the various types of storms from the Gulf of Mexico and Atlantic Ocean have high R-factor values. The coastal regions of the Gulf of Mexico and Atlantic Ocean have a long history of hurricanes and tropical storms, as the climatologically warm seawater provides an abundant energy source for intense storms during the hurricane season from May to November (Jarvinen et al., 1984; Maloney and Hartmann, 2000). Thus, hurricanes and tropical storms could easily move into the inland areas and deliver heavy rainfalls, owing to the warm sea temperature and flat terrain (Bales, 2003; Stanturf et al., 2007). Except for the regions mentioned above, the spatial patterns of the R-factor are homogeneous over the United States, and the R-factors are not excessively high compared to the coastal regions.

Figure 4

Fig. 4 shows the monthly rainfall erosivity maps. The intensity of the monthly R-factor apparently varies with the regional seasonality. For example, the west coastal region showed high rainfall erosivity during a winter season from November to March, and the R-factor was identified in December. However, during the summer and early fall seasons from June to September, the rainfall erosivity was low and spatially homogeneous. In addition, the monthly rainfall erosivity maps exhibited a smooth decrease in the R-factor from winter to spring, followed by lower homogeneous values in summer, and then a smooth increase in fall. As expected, the results suggest that the trend of rainfall erosivity is affected by the seasonality, as is the case with precipitation. In the coastal and inland regions near the Gulf of Mexico, the spatial distribution of the R-factor was inhomogeneous, and the value was very high from June to December. The period from June to September showed conflicting tendencies in rainfall erosivity between the western and eastern coastal regions. In addition, the R-factors in the Florida Peninsula were significantly higher from June to September.

3.2 Attributes of Rainfall Erosivity on Hydrological Basins and Climate Zones

The rainfall erosivity map was further analyzed in the context of hydrological unit basins and climatological zones. For this purpose, the hydrologic unit code-2 (HUC, https://water.usgs.gov//GIS/huc.html) and climate features (hereinafter referred to as climate zones) developed by Wladimir Köppen (Kottek et al., 2006) were used. This section addresses the analysis results for the hydrological unit basins. Fig. 5 shows the HUC boundary (the upper left), its area distribution (the upper right), and R-factors (the bottom). The HUC includes the Tennessee region, i.e., the smallest basin (105,949 sq. km), and the Missouri region, i.e., the biggest basin (1,349,418 sq. km, or 15% of the total area).

Figure 5

The range of the R-factors varies with the location of the basin. The ‘a’-‘h’ (except ‘d’ and ‘g’) basins, located on the Florida Peninsula and influenced by the climates of the Atlantic Ocean and Gulf of Mexico, have high rainfall erosivity. ‘h’ (lower Mississippi region) represents the basin where the highest R-factor was identified. However, the ‘n’ (upper Colorado region), ‘o’ (lower Colorado region), and ‘p’ (great basin region) basins had relatively low values of the R-factor. Considering the ranges of the R-factors in the three basins, the spatial distributions of the R-factors in these basins were considerably homogenous. ‘j’ (Missouri region), the largest basin in the United States, had a relatively narrow range for the R-factor, indicating a low variation and spatially homogeneous distribution. Both ‘k’ (Arkansas-White-Red region) and ‘i’ (Texas-Gulf region) were smaller than ‘j’; both basins had a wider range of the R-factors than ‘j’, and spatially inhomogeneous distributions.

Figure 6

Fig. 6 illustrates the results for monthly R-factors by basin, to show the seasonal patterns of the R-factors. Most basins showed a change of rainfall erosivity with season. In particular, some basins (‘a’-‘i’) located on the east coast line had a high rainfall erosivity from June to September, whereas it was low in January, February, and December. Basins (‘q’ and ‘r’) located on the west coastline showed a high rainfall erosivity during the winter season (from November to March), but showed a low rainfall erosivity during the warm season (from April to September). ‘h’ had high R-factor values for all months. Compared with other basins, ‘c’ (South Atlantic-Gulf region) had the highest values of the R-factor from June to September. The monthly R-factors of ‘n’, ‘o’, and ‘p’ were consistent, as the range was only from 3 to 52, and it was not varied from month-to-month. These results suggest that those basins show no seasonality in rainfall erosivity.

The rainfall erosivity map is also analyzed based on climate zones. Fig. 7 shows a map of climate zones in the United States, and the distribution of the R-factor by the climate zones. Over the CONUS, five (Cfa, BSk, Dfb, Dfa, and Csb) of climate zones are complexly distributed in the western region, whereas three (Cfa, Dfa, and Dfb) climate zones are homogeneously distributed in the eastern region (depending on the latitude).

Figure 7

The tropical climate zones have the highest R-factor, followed by the temperate, cold, and arid climate groups. On average, 45 annual mean storm events with sufficient intensity to erode soil were observed in the tropical climate group (covering most of the southern Florida Peninsula). This was 1.5 times higher than the number of annual mean storm events in the United States. The temperate climate zones (covering most of the regions affected by storms from the Gulf of Mexico and Atlantic Ocean) had relatively high rainfall erosivity. Moreover, 15 of the annual mean storm events were observed in the arid climate group, which showed the lowest rainfall erosivity within 15 of the climate zones. That was only approximately half the number of annual mean storm events in the United States.

Figure 8

Fig. 8 shows the monthly rainfall erosivity by climate zone. The seasonality of the R-factor was clearly visible in the tropical climate group. The high values of the R-factor (mean = 492 MJ mm ha^{-1} hr^{-1} month^{-1}) were identified during the wet season from June to September, whereas the low values of the R-factor (mean = 108 MJ mm ha^{-1} hr^{-1} month^{-1}) were found during a dry season from November to April. However, the arid climate zone showed no seasonality in regards to the rainfall erosivity.

3.3 Comparison with the Ground-Based Rainfall Erosivity Map

To evaluate the rainfall erosivity map developed in this study, it was compared to a rainfall erosivity map based on rain-gauge data (Fig. 9). Panagos et al. (2017) developed a global rainfall erosivity map using high-resolution rain-gauge data collected from 65 countries as a reference. For the United States, they employed 92 pieces of gauge data over 11 years (2006–2016). The average density of the observation stations was one every 83,303 km^2. They used a Gaussian process regression model to interpolate the R-factor point values to a map at a 1 km × 1 km spatial resolution. This map is available from the European Soil Data Centre (https://esdac.jrc.ec.europa.eu/content/global-rainfall-erosivity).

Figure 9

The range of the R-factors in Panagos et al. (2017) is 6–9,645 MJ mm ha^{-1} h^{-1} yr^{-1}, and the mean value is 2,067 MJ mm ha^{-1} h^{-1} yr^{-1}, i.e., 1.65 times higher than the mean R-factor estimated in this study. In Fig. 9, the western north region (a), middle region (b), and coastal and inland region near by Gulf of Mexico (c) were highlighted for comparison. The R-factors in box (a), as estimated in this study, are higher than those from Panagos et al. (2017). Considering the comparison result of the annual precipitations in Fig. 8, this result demonstrates that the R-factors calculated by Panagos et al. (2017) were far more underestimated than those in this study. This is because Panagos et al. (2017) only used three rain-gauge sites to cover the region. Notably, the spatial distribution of the rainfall erosivity estimated in this study is more seamless than that in Panagos et al. (2017), even though the spatial resolution of this study (8 × 8 km) is coarser than that of Panagos et al. (2017) (1 × 1 km), especially for the box (c) regions close to the Gulf of Mexico. This result exhibits the typical limitations in using rain-gauge data and interpolation methods for predicting R-factors in ungauged areas.

The bottom-left panel in Fig. 9 shows a comparison of R-factor samplings extracted from 10,000 random points. The R-squared value is 0.64, and the bias is 64%. Based on the Y-axis (the R-factors of Panagos et al. (2017)), the bias is 88.1% when the R-factor is smaller than 2,000, whereas the bias is 55.6% when the R-factor is greater than 2,000. This result suggests that the larger the estimated R-factors, the higher the uncertainty. Considering that the R-factors greater than 2,000 are mostly from the coastal regions, data assimilation with high-density rain-gauge data might be necessary in these regions to improve the accuracy of the predicted R-factor.

4. Discussion

4.1 The CMORPH for Mapping Rainfall Erosivity

With regard to hydrologic applications, many studies have evaluated the CMORPH product against ground-based observations and "Next Generation Weather Radar" Stage IV (radar-based and gauge-adjusted) as reference data (Derin et al., 2016). According to AghaKouchak et al. (2011) and Romilly and Gebremichael (2011), the CMORPH data is superior to that from other satellite precipitation products (e.g., "PERSIANN," "TMPA-RT," and TMPA-V6) with respect to the probability of detecting extremes and the volume of correctly identified precipitation. When applying CMORPH in Ethiopian river basins, the volume of precipitation tends to be underestimated by 11%, and the bias depends on the rainfall regime and topographical characteristics. Habib et al. (2012) evaluated the CMORPH using dense ground observations in south Louisiana, and suggested that the CMORPH product has high detection skills. In particular, they suggested that the probability of successful detection is approximately 80% for surface rain rates >2 mm/h, the probability of false detection is <3%, and the CMORPH has a negligible bias. However, they also concluded that the accuracy of the CMORPH products varied with temporal resolution, region, and season.

Figure 10

As the CMORPH is a satellite-based precipitation product, it might incorporate several uncertainties that might influence the estimation and mapping of the R-factors. In this study, we intend to highlight two issues: overestimated precipitation on water bodies (e.g., lakes and reservoirs), and the accuracy of annual precipitation. It is well-known that satellite-based precipitation products are likely to overestimate precipitation where lakes and reservoirs are located (Tian and Peters-Lidard, 2007). This fact is also confirmed in this study. Fig. 10 shows (a) a map showing the locations of water bodies on the annual precipitation field, and (b) the rainfall erosivity map. It is found that the annual precipitation on water bodies is abnormally higher than in other areas. It is also confirmed that the R-factor result shows the same trend for water bodies. In view of this attribute of the CMORPH precipitation product, this study excluded the abnormally overestimated R-factors for water bodies from further analysis.

To briefly verify the accuracy of the CMORPH precipitation, this study compared the CMORPH and "PRISM" (http://www.prism.oregonstate.edu/), a rain gauge-based precipitation product. Fig. 11 shows three comparison results: spatial distributions (top left panel), probability density functions (top right panel), and samples extracted from 10,000 random points (bottom panel).

Figure 11

In the spatial distribution maps, three regions are selected, i.e., boxes (a), (b), and (c). Overall, the trends of the spatial distributions are similar to each other, and the correlation of the two maps reaches as high as 0.71. In the case of box (b), in the middle of the country, and box (c), affected by Atlantic Ocean and Gulf of Mexico, both annual precipitation maps show similar patterns of spatial distributions and PDFs (top panels). However, box (a), close to the Pacific Ocean, shows that the CMORPH was underestimated as compared to that of PRISM, and the difference was up to approximately double. Considering this result, the rainfall erosivity map based on the CMORPH has a higher possibility of underestimation around the region. Data assimilation with rain-gauge data might be a way to overcome this limitation of the CMORPH, and to improve the quantitative accuracy of the precipitation product for mapping rainfall erosivity. As this topic is challenging and out of scope for this study, we leave this issue for future study.

According to the result in Fig. 11 (bottom panel), the R-squared value is as high as 0.67 and the bias is 84%, indicating an ideal case. It is confirmed that the scatter samples where the PRISM is greater than the CMORPH are mostly extracted from box (a). Thus, the accuracy of satellite-based precipitation data can be lower than that of the rain-gauge data, but can help overcome the aforementioned limitations in the rain-gauge data. Considering the pace of technological developments in satellite observation systems and data quality improvements, satellite-based precipitation data should be the best alternative to a ground-based observation system in the future.

4.2 Potential Benefit of the Rainfall Erosivity Map in Practice

Considering the effects of soil erosion by rainfall on the entire environment, it is expected that the rainfall erosivity map developed in this study can be used to estimate amounts of soil loss, and to identify regions vulnerable to soil erosion. The 1972 amendments to the Clean Water Act (CWA) prohibit the discharge of any pollutant into navigable waters, unless the discharge is authorized by a National Pollutant Discharge Elimination System (NPDES) permit. As construction site stormwater runoff can contribute significantly to water quality problems, the Phase I Stormwater Rule required that all construction sites with a planned land disturbance of five acres or more must obtain an NPDES permit and implement stormwater runoff control plans. Phase II extended the requirements of the stormwater program to sites between 1–5 acres (EPA, 2012). The rainfall erosivity waiver allows the permitting authorities to waive the requirements for those sites that do not have adverse water quality impacts. The United States Environmental Protection Agency (EPA) NPDES has developed a web-based R-factor estimation tool for users attempting to implement the CWA (https://www.epa.gov/waterdata/rainfall-erosivity-factor-calculator). However, it is questionable whether the tool can estimate a proper R-factor in a certain area, as the tool is based on rain-gauge data and a spatial interpolation method. Therefore, at this point, the rainfall erosivity map developed in this study could practically improve or replace the EPA NPDES R-factor map.

5. Conclusions

This study suggested a new approach for mapping rainfall erosivity using a high-resolution satellite-based precipitation product, and applied it to the CONUS. The rainfall erosivity map was analyzed in terms of different temporal resolutions (e.g., monthly and annual rainfall erosivity), hydrological unit basins, and climate zones. Based on the results, we concluded as follows:

- Using the CMORPH (a high-resolution satellite-based data) to map rainfall erosivity has strengths and weaknesses. The CMORPH was able to apply the standard method to estimate a relatively accurate R-factor, and to map a seamless rainfall erosivity without employing an interpolation method. These merits were useful for understanding the spatial variability of rainfall erosivity, and for identifying regions vulnerable to soil erosion by rainfall. However, the CMORPH precipitation product might require correction for some coastal regions to improve the rainfall erosivity map.
- From the rainfall erosivity map, the mean of the rainfall erosivity was 1,260 MJ mm ha^{-1} h^{-1} yr^{-1}, with high variability ranging from 33 to 6,000 MJ mm ha^{-1} h^{-1} yr^{-1}, depending on the region of the United States. The coastal regions near the Pacific Ocean, Gulf of Mexico, and Atlantic Ocean have the highest 20% of rainfall erosivity. The seasonality of rainfall erosivity was confirmed through the monthly rainfall erosivity maps. Most coastal regions are vulnerable to soil erosion by rainfall, depending on their typical rainy seasons. In addition, climate features have a strong relation with rainfall erosivity, and the spatial pattern of rainfall erosivity varies within climate zones. The rainfall erosivity in the tropical climate group was relatively higher than that in the other groups, whereas the arid climate group presented very low and spatially homogeneous rainfall erosivity. Soil loss should be monitored in coastal regions, and construction areas should be thoroughly examined in the southern Florida Peninsula belonging to the tropical climate group.

Finally, considering the pace of technological developments in satellite observation systems and data quality improvements, satellite-based rainfall erosivity maps represent the best alternative to ground-based rainfall erosivity maps in the future.

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References

AghaKouchak, A., Behrangi, A., Sorooshian, S., Hsu, K., Amitai, E., 2011. Evaluation of satellite-retrieved extreme precipitation rates across the central United States. J. Geophys. Res. 116, D02115. https://doi.org/10.1029/2010JD014741.

Ahn, K. H., Palmer, R. N., 2015. Trend and variability in observed hydrological extremes in the United States. J. Hydrol. Eng. 21(2), 04015061. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001286.

Anagnostou, E. N., Maggioni, V., Nikolopoulos, E. I., Meskele, T., Hossain, F., Papadopoulos, A., 2010. Benchmarking high-resolution global satellite rainfall products to radar and rain-gauge rainfall estimates. IEEE T. Geosci. Remote. 48(4), 1667-1683. 10.1109/TGRS.2009.2034736.

Angulo-Martínez, M., Beguería, S., 2009. Estimating rainfall erosivity from daily precipitation records: A comparison among methods using data from the Ebro Basin (NE Spain). J. Hydrol. 379(1-2), 111-121. https://doi.org/10.1016/j.jhydrol.2009.09.051.

Arnoldus, H.M.J., 1977. Methodology used to determine the maximum potential average annual soil loss due to sheet and rill erosion in Marocco. FAO Soils Bull. 34, 83.

Bales, J. D., 2003. Effects of hurricane floyd inland flooding, September–October 1999, on tributaries to Pamlico Sound, North Carolina. Estuaries, 26(5), 1319-1328.

Ballabio, C., Borrelli, P., Spinoni, J., Meusburger, K., Michaelides, S., Beguería, S., Klik, A., Petan, S., Janeček, M., Olsen, P., Aalto, J., 2017. Mapping monthly rainfall erosivity in Europe. Sci. Total. Environ. 579, 1298-1315. https://doi.org/10.1016/j.scitotenv.2016.11.123.

Bertol, I., Leite, D., Engel, F.L., Cogo, N.P., González, A.P., 2007. Erodibility of a typichapludox evaluated underfield conditions. Revista Brasileira de Ciência do Solo31, 541–549. http://dx.doi.org/10.1590/S0100-06832007000300014.

Bonilla, C. A., Vidal, K. L., 2011. Rainfall erosivity in central Chile. J. Hydrol. 410(1-2), 126-133. https://doi.org/10.1016/j.jhydrol.2011.09.022.

Brown, L. C., Foster, G. R., 1987. Storm erosivity using idealized intensity distributions. T. ASAE. 30(2), 379-0386. https://doi.org/10.13031/2013.31957.

Buytaert, W., Celleri, R., Willems, P., De Bievre, B., Wyseure, G., 2006. Spatial and temporal rainfall variability in mountainous areas: A case study from the south Ecuadorian Andes. J. Hydrol. 329(3-4), 413-421. https://doi.org/10.1016/j.jhydrol.2006.02.031.

Chen, H., Chandrasekar, V., Cifelli, R., Xie, P., 2019. A Machine Learning System for Precipitation Estimation Using Satellite and Ground Radar Network Observations, IEEE Trans. Geosci. Remote Sens. https://doi.org/10.1109/TGRS.2019.2942280.

Conner, W. H., Day, J. W., Baumann, R. H., Randall, J. M., 1989. Influence of hurricanes on coastal ecosystems along the northern Gulf of Mexico. Wetl. Ecol. Manag. 1, 45–56. https://doi.org/10.1007/BF00177889.

Cooper, K., 2011. Evaluation of the relationship between the RUSLE R-factor and mean annual precipitation. Research Report, Colorado State University: https://www.engr.colostate.edu/~pierre/ce_old/Projects/linkfiles/Cooper%20R-factor-Final.pdf.

Da Silva, A. M., 2004. Rainfall erosivity map for Brazil. Catena 57(3), 251-259. https://doi.org/10.1016/j.catena.2003.11.006.

Derin, Y., Anagnostou, E., Berne, A., Borga, M., Boudevillain, B., Buytaert, W., Chang, C.H., Delrieu, G., Hong, Y., Hsu, Y.C. and Lavado-Casimiro, W., Mane, B., Moges, S., Nikolopoulos, E. I., Sahlu, D., Salerno, F., Juan-Pablo Rodríguez-Sánchez, Vergara, H. J., Yilmaz, K. K., 2016. Multiregional satellite precipitation products evaluations over complex terrain. J. Hydrometeorol. 17, 1817-1836. https://doi.org/10.1175/JHM-D-15-0197.1.

Elbasit, A. M. A., Huang, J., Ojha, C. S. P., Yasuda, H., Adam, E. O., 2013. Spatiotemporal changes of rainfall erosivity in Loess Plateau. China. ISRN Soil Science. 2013. http://dx.doi.org/10.1155/2013/256352.

Elwell, H. A., Stocking, M. A., 1976. Vegetal cover to estimate soil erosion hazard in Rhodesia. Geoderma. 15(1), 61-70. https://doi.org/10.1016/0016-7061(76)90071-9.

Fournier, F., 1956. The effect of climatic factors on soil erosion. Estimates of solids transported in suspension in runoff. Ass. Int. Hydrol. Publ. 38, 6.

Fournier, F., 1960. Climat er Erosion, Pressess Universitaires de France, Paris.

Goovaerts, P., 1999. Using elevation to aid the geostatistical mapping of rainfall erosivity. Catena 34(3-4), 227-242. https://doi.org/10.1016/S0341-8162(98)00116-7.

Habib, E., Haile, A. T, Tian, Y., Joyce, R. J., 2012. Evaluation of the high-resolution CMORPH satellite rainfall product using dense rain gauge observations and radar-based estimates. J. Hydrometeorol. 13, 1784-1798. https://doi.org/10.1175/JHM-D-12-

017.1.

Han, H., Kim, J., Chandrasekar, V., Choi, J., Lim, S., 2019. Modeling streamflow enhanced by precipitation from atmospheric river using the NOAA national water model: a case study of the Russian river basin for February 2004. Atmos. 10 (8), 466. https://doi.org/10.3390/atmos10080466.

Hernando, D., Romana, M. G., 2015. Estimating the rainfall erosivity factor from monthly precipitation data in the Madrid Region (Spain). J. Hydrol. Hydromech., 63 (1), 55-62. https://doi.org/10.1515/johh-2015-0003.

Hoyos, N., Waylen, P.R., Jaramillo, A., 2005. Seasonal and spatial patterns of erosivity ina tropical watershed of the Colombian Andes. J. Hydrol. 314, 177–191. http://dx.doi.org/10.1016/j.jhydrol.2005.03.014.

Hudson, N., 1971. Soil Conservation. Cornell University Press, Ithaca.

Jarvinen, B. R., Neumann, C. J., Davis, M. A., 1984. A tropical cyclone data tape for the North Atlantic Basin, 1886-1983: Contents, limitations, and uses.

Jayawardena, A. W., Rezaur, R. B., 2000. Drop size distribution and kinetic energy load of rainstorms in Hong Kong. Hydrol. Process. 14(6), 1069-1082. https://doi.org/10.1002/(SICI)1099-1085(20000430)14:6<1069::AID-HYP997>3.0.CO;2-Q.

Joyce, R. J., Janowiak, J. E., Arkin, P. A., Xie, P., 2004. CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. J. Hydrometeorol. 5(3), 487-503. https://doi.org/10.1175/1525-7541(2004)005<0487:CAMTPG>2.0.CO;2.

Khorsandi, N., Mahdian, M. H., Pazira, E., Nikkami, D., Chamheidar, H., 2012. Comparison of Different Interpolation Methods for Investigating Spatial Variability of Rainfall Erosivity Index. Pol. J. Environ. Stud. 21(6).

Kim, J., Yoo, C., 2014. Use of a dual Kalman filter for real-time correction of mean field bias of radar rain rate. J. Hydrol. 519(Part D), 2785-2796. http://doi.org/10.1016/j.jhydrol.2014.09.072.

Kim, J., Yoo, C., Lim, S., Choi, J., 2015. Usefulness of relay-information-transfer for radar QPE. J. Hydrol. 531, 308-319. https://doi.org /10.1016/j.jhydrol.2015.07.006.

Klik, A., Haas, K., Dvorackova, A., Fuller, I. C., 2015. Spatial and temporal distribution of rainfall erosivity in New Zealand. Soil. Res. 53(7), 815-825. https://doi.org/10.1071/SR14363.

Knight, D. B., Davis, R. E., 2007. Climatology of tropical cyclone rainfall in the southeastern United States. Phys. Geogr., 28(2), 126-147. https://doi.org/10.2747/0272-3646.28.2.126

Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel F., 2006. World Map of the Köppen-Geiger climate classification updated. Meteorol. Z. 15, 259-263. https://doi.org/10.1127/0941-2948/2006/0130.

Krauer, J., 1988. Rainfall, erosivity and isoerodent map of Ethiopia.

Lal, R., 1976. Soil erosion on alfisols in Western Nigeria III–Effects of rainfall characteristics. Geoderma 16, 389–401. http://dx.doi.org/10.1016/0016-7061(76)90003-3.

Lal, R., 2005. Soil erosion and carbon dynamics, Soil. Till. Res. 81(2), 137-142. https://doi.org/10.1016/j.still.2004.09.002.

Lee, J., Heo, J., 2011. Evaluation of estimation methods for rainfall erosivity based on annual precipitation in Korea, J. Hydrol. 409, 30-48. https://doi.org/10.1016/j.jhydrol.2011.07.031.

Lee, M. H., Lin, H. H., 2015. Evaluation of annual rainfall erosivity index based on daily, monthly, and annual precipitation data of rainfall station network in Southern Taiwan. International Journal of Distributed Sensor Networks, 11(6), 214708.

https://doi.org/10.1155/2015/214708.
Lenvain, J. S., Sakala, W. K., Pauwelyn, P. L. L., 1988. Iso-erodent map of Zambia: Part II: Erosivity prediction and mapping. Soil. Technol. 1(3), 251-262. https://doi.org/10.1016/0933-3630(88)90024-4.
Leow, C. S., Ghani, A. A., Zakaria, N. A., Abidin, R. Z., 2011. Development of rainfall erosivity isohyet map for Peninsular Malaysia. In 3rd International Conference on Managing Rivers in the 21st Century: Sustainable Solutions for Global Crisis of Flooding, Pollution and Water Scarcity, 748-756.
Lombardi Neto, F., Moldenhauer, W.C., 1992. Rainfall erosivity—its distribution andrelationship with soil loss at Campinas, state of São Paulo, Brazil. Bragantia, 51, 189–196. http://dx.doi.org/10.1590/S0006-87051992000200008.
LOWLAND, P. O. S. S., 2005. Artificial neural networks use for rainfall-runoff erosivity factor estimation. Environ. Dev. 8(1), 04.
Maloney, E. D., Hartmann, D. L., 2000. Modulation of eastern North Pacific hurricanes by the Madden–Julian oscillation. J. climate, 13(9), 1451-1460.
Marques, M.J., Bienes, R., Jimenez, L., Perez-Rodriguez, R., 2007. Effect of vegetal cover onrunoff and soil erosion under light intensity events. Rainfall simulation over USLEplots. Sci. Total Environ. 378 (1–2), 161–165. https://doi.org/10.1016/j.scitotenv.2007.01.043.
Meddi, M., Toumi, S., Assani, A. A., 2016. Spatial and temporal variability of the rainfall erosivity factor in Northern Algeria. Arab. J. Geosci. 9(4), 282. https://doi.org/10.1007/s12517-015-2303-8.
Meusburger, K., Steel, A., Panagos, P., Montanarella, L., Alewell, C., 2012. Spatial and temporal variability of rainfall erosivity factor for Switzerland. Hydro. Earth. Syst. SC. 16(1), 167-177. doi:10.5194/hess-16-167-2012.

Mikhailova, E. A., Bryant, R. B., Schwager, S. J., Smith, S. D., 1997. Predicting rainfall erosivity in Honduras. Soil. Sci. Soc. Am. J. 61(1), 273-279. https://doi.org/10.2136/sssaj1997.03615995006100010039x.

Nearing, M. A., Lane, L. J., Lopes, V. L., 1994. Modeling soil erosion. Soil erosion research methods. 2, 127-156.

Nesbitt, S. W., Anders, A. M., 2009. Very high resolution precipitation climatologies from the Tropical Rainfall Measuring Mission precipitation radar. Geophys. Res. Lett. 36(15). https://doi.org/10.1029/2009GL038026.

Niedermeier, C., 1998. Soil erosion modeling using GIS.

Oduro-Afriyie, K., 1996. Rainfall erosivity map for Ghana. Geoderma. 74(1-2), 161-166. https://doi.org/10.1016/S0016-7061(96)00054-7.

Oduro-Afriyie, K., 1998. Rainfall erosivity map for West Africa. J. Appl. Sci. Tech. 3(1-2), 92-101.

Oliveira, P. T. S., Wendland, E., Nearing, M. A., 2013. Rainfall erosivity in Brazil: A review. Catena, 100, 139-147. https://doi.org/10.1016/j.catena.2012.08.006.

Panagos, P., Ballabio, C., Borrelli, P., Meusburger, K., Klik, A., Rousseva, S., Tadić, M.P., Michaelides, S., Hrabalíková, M., Olsen, P., Aalto, J., Lakatos, M., Rymszewicz, A., Dumitrescu, A., Beguería, S., Alewell, C., 2015. Rainfall erosivity in Europe. Sci. Total Environ. 511, 801-814. https://doi.org/10.1016/j.scitotenv.2015.01.008.

Panagos, P., Ballabio, C., Borrelli, P., Meusburger, K., 2016a. Spatio-temporal analysis of rainfall erosivity and erosivity density in Greece. Catena 137, 161-172. https://doi.org/10.1016/j.catena.2015.09.015.

Panagos, P., Borrelli, P., Spinoni, J., Ballabio, C., Meusburger, K., Beguería, S., Klik, A., Michaelides, S., Petan, S., Hrabalíková, M., Olsen, P., Aalto, J., Lakatos, M., Rymszewicz, A., Dumitrescu, A., Tadi´c, M. P., Diodato, N., Kostalova, J., Rousseva, S., Banasik, K., Alewell, C., 2016b. Monthly rainfall erosivity: conversion factors for different time resolutions and regional assessments. Water. 8(4), 119. https://doi.org/10.3390/w8040119.

Panagos, P., Borrelli, P., Meusburger, K., Yu, B., Klik, A., Lim, K.J., Yang, J.E., Ni, J., Miao, C., Chattopadhyay, N., Sadeghi, S.H., Hazbavi, Z., Zabihi, M., Larionov, G. A., Krasnov, S. F., Gorobets, A. V., Levi, Y., Erpul, G., Birkel, C., Hoyos, N., Naipal, V., Oliveira, P. T. S., Bonilla, C. A., Meddi, M., Nel, W., Dashti, H. A., Boni, M., Diodato, N., Oost, K. V., Nearing, M., Ballabio, C., 2017. Global rainfall erosivity assessment based on high-temporal resolution rainfall records. Sci Rep. DOI:10.1038/s41598-017-04282-8.

Ralph, F.M., Neiman, P.J., Wick, G.A., Gutman, S.I., Dettinger, M.D., Cayan, D.R., White, A.B., 2006. Flooding on California's Russian River: Role of atmospheric rivers. Geophys. Res. Lett., 33. https://doi.org/10.1029/2006GL026689.

Ramos, M. C., Durán, B., 2014. Assessment of rainfall erosivity and its spatial and temporal variabilities: Case study of the Penedès area (NE Spain). Catena, 123, 135-147. https://doi.org/10.1016/j.catena.2014.07.015.

Renard, K. G., Freimund, J. R., 1994. Using monthly precipitation data to estimate the R-factor in the revised USLE. J. Hydrol. 157(1-4), 287-306. https://doi.org/10.1016/0022-1694(94)90110-4.

Renard, K. G., Foster, G. R., Weesies, G. A., Porter, J. P., 1991. RUSLE: Revised universal soil loss equation. J. Soil. Water. Conserv. 46(1), 30-33.

Renard, K.G., Foster, G. R., Weesies, G. A., McCool, D. K., Yoder, D. C., 1997. Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation. USDA Handbook No. 703, USDA: Washington, DC.

Romilly, T. G., Gebremichael, M., 2011. Evaluation of satellite rainfall estimates over

Ethiopian river basins. Hydrol. Earth. Syst. Sc. 15, 1505-1514. doi:10.5194/hess-15-1505-2011.

Roose, E. J., 1977. Use of the universal soil loss equation to predict erosion in West Africa. In Soil erosion: prediction and control. Soil Conservation Society of America Ankeny, IA. 21, 60-74.

Seaber, P.R., Kapinos, F.P., Knapp, G.L., 1987. Hydrologic Unit Maps: U.S. Geological Survey Water-Supply Paper. 2294, 63.

Smith, S.V., Renwick, W.H., Buddemeier, R.W., Crossland, C.J., 2001. Budgets of soil erosion and deposition for sediments and sedimentary organic carbon across the conterminous United States. Glob. Biogeochem. Cycles. 15, 697–707. https://doi.org/10.1029/2000GB001341.

Stanturf, J. A., Goodrick, S. L., Outcalt, K. W., 2007. Disturbance and coastal forests: a strategic approach to forest management in hurricane impact zones. Forest Ecol Manag, 250(1-2), 119-135.

Stocking, M.A. and Elwell, H.A., 1973. Prediction of subtropical storm losses from field plot studies. Agric. Meteorol. 12, 193-201. https://doi.org/10.1016/0002-1571(73)90019-8.

Tian, Y., Peters-Lidard, C. D., 2007. Systematic anomalies over inland water bodies in satellite-based precipitation estimates. Geophys Res Lett., 34(14).

Ufoegbune, G. C., Bello, N. J., Ojekunle, Z. O., Orunkoye, A. R., Eruola, A. O., Amori, A. A., 2011. Rainfall erosivity pattern of Ogun River basin area (Nigeria) using modified Fournier index. Eur Water, 35, 23-29.

United States Environmental Protection Agency (EPA)., 2012. Stormwater phase II final rule, construction rainfall erosivity waiver, Washington, DC, USA, EPA 833-F-00-014.

Van Dijk, A. I. J. M., Bruijnzeel, L. A., Rosewell, C. J., 2002. Rainfall intensity–kinetic energy relationships: a critical literature appraisal. J. Hydrol. 261(1-4), 1-23.

https://doi.org/10.1016/S0022-1694(02)00020-3.

Vrieling, A., Sterk, G., de Jong, S. M., 2010. Satellite-based estimation of rainfall erosivity for Africa. J. Hydrol. 395, 235-241. https://doi.org/10.1016/j.jhydrol.2010.10.035.

Wang, G., Gertner, G., Singh, V., Shinkareva, S., Parysow, P., Anderson, A., 2002. Spatial and temporal prediction and uncertainty of soil loss using the revized universal soil loss equation: a case study of the rainfall–runoff erosivity R factor. Ecol Model. 153, 143–155. https://doi.org/10.1016/S0304-3800(01)00507-5.

Wischmeier, W. H., Smith, D. D., 1958. Rainfall energy and its relationship to soil loss. Eos, Transactions American Geophysical Union. 39(2), 285-291. https://doi.org/10.1029/TR039i002p00285.

Wischmeier, W.H., Smith, D.D., 1965. Rainfall-Erosion Lossess from Cropland East of the Rocky Mountains:Guide for selection of practices for soil and water conservation. USDA Agric. Handbook, No 282, Washington, D.C.

Wischmeier, W. H., Smith, D. D., 1978. Predicting rainfall erosion losses-a guide to conservation planning. Predicting rainfall erosion losses-a guide to conservation planning.

Xie, P., Joyce, R., Wu, S., Yoo, S. H., Yarosh, Y., Sun, F., Lin, R. 2017. Reprocessed, bias-corrected CMORPH global high-resolution precipitation estimates from 1998. J. Hydrometeorol. 18(6), 1617-1641. https://doi.org/10.1175/JHM-D-16-0168.1.

Yin, S., Xie, Y., Nearing, M. A., Wang, C. 2007. Estimation of rainfall erosivity using 5 to 60-minute fixed-interval rainfall data from China. Catena 70(3), 306-312. https://doi.org/10.1016/j.catena.2006.10.011.

Zhu, Q., Chen, X., Fan, Q., Jin, H., Li, J., 2011. A new procedure to estimate the rainfall erosivity factor based on Tropical Rainfall Measuring Mission (TRMM) data. Sci. China. Tech. Sci. 54(9), 2437. https://doi.org/10.1007/s11431-011-4468-z.

Environmental Policies and Political Feasibility: Eco-Labels versus Emission Taxes

by

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Abstract: This paper examines the economic and political implications of two market-based policies, eco-certifications and emission taxes. We evaluate each policy's effects on the environment, investment in clean technology, and social welfare under imperfect competition. We find that eco-certification reduces total damage to the environment, increases consumer benefits, and is socially desirable. However, polluting firms will never voluntarily accept the socially optimal eco-standard, leading to suboptimal certification programs. Unless the marginal damage to the environment from emissions is sufficiently low and demand is sufficiently large, environmental damage occurring under voluntary eco-certification is higher in comparison to alternative policies. We examine the welfare impacts of each policy to identify social preferences. Using realized market benefits to construct policy preferences, we show conditions under which the socially optimal environmental policy is unlikely to be politically feasible. Our results explain the popularity and suboptimal qualities of eco-certification programs.

Keywords: Eco-certification, Emission taxes, Environmental regulations, Green consumers
JEL codes: H23, Q5, D62, D43, Q58

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