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Towards large-scale monitoring of soil erosion in Africa: Accounting for the dynamics of rainfall erosivity

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ABSTRACT

Soil erosion by water occurs on sloped terrain when erosive rainfall and consequent surface runoff act on soils that are not well-protected by vegetation or other soil protective measures. Both rainfall erosivity and vegetation cover are highly variable through space and time. Joint accounting for the variability of these factors is required to effectively map and monitor soil erosion. However, most studies merely use average annual erosivity values, partly due to data paucity. This study analyses the variability of rainfall erosivity across Africa through the use of 3-hourly TRMM Multi-satellite Precipitation Analysis (TMPA) precipitation data. We obtained average annual erosivity estimates from 15 yr of TMPA data (1998–2012) using intensity–erosivity relationships. Our estimates showed a positive correlation ($r = 0.84$) with long-term annual erosivity values of 37 stations obtained from literature. Our TMPA-analysis confirmed and mapped the large interannual variability, with maximum annual erosivity often exceeding two to three times the mean value, especially in semi-arid areas. Seasonal variability of erosivity was investigated from TMPA-based average monthly erosivity estimates, which resulted in similar seasonal patterns as those reported in literature. We conclude that (1) spatial and temporal variability of erosivity is important and needs to be accounted for in combination with vegetation cover when monitoring soil erosion; and (2) 3-hourly TMPA data allow for a good first estimate of the variability of erosivity in Africa, which could be improved by upcoming techniques that provide more accurate rainfall information at higher spatial and temporal resolutions.

1. Introduction

Soil erosion by water reduces soil quality and as such jeopardizes important ecosystem services that soils provide (Karlen et al., 2003). These include among others carbon sequestration, flood control, and food production. The demands for such services increase due to global processes like population growth and changes in consumption patterns (Tilman et al., 2001). This increasing demand is clearly illustrated in Africa by the strong interest of foreign investors to secure land resources for food or biofuel production (Zoomers, 2010; Borras et al., 2011), in combination with the large expected growth of the African population (Cleland, 2013). Soil erosion could aggravate in the future either through a mis- or overutilization of the soil resource, or through climate change (Alcamo et al., 2005). Given the importance of the services that soils provide globally, large-scale monitoring of soil erosion is required to understand and mitigate its effects under changing conditions.

Soil erosion occurs on sloped terrain when rainfall and consequent surface runoff act on soils that are poorly protected by vegetation cover or other protective measures (Lal, 2001). Much erosion occurs during single rainfall events of high intensity, particularly when vegetation cover is sparse (Stocking, 1999). Terrain characteristics are more stable in time, while soil erodibility may show large variability as well due to natural or human disturbance, biological activity and erosion itself (Weltz et al., 1998; Cantón et al., 2009). Whereas it is typically difficult to obtain accurate timely data on soil erodibility for larger areas, significant efforts are done to obtain information on rainfall (Kidd and Levizzani, 2011) and vegetation cover (Jensen, 2007) from satellite data. Joint assessment of these two dynamic factors could provide useful input to monitoring soil erosion. A literature review on the use of satellite data for erosion studies indicated that many studies have assessed vegetation cover and its variability for larger areas (>100 km^2), but large-scale evaluations of the erosive force of rainfall and its variability are rare (Vrieling, 2006).

Rainfall erosivity is the term used to refer to the erosive force of rainfall and the consequent runoff. This erosive force involves the detachment of soil particles by the kinetic energy from falling raindrops, and the transport of these soil particles through surface runoff. The most common index to quantify rainfall erosivity is the *R*-factor of the widely-used Universal Soil Loss Equation (USLE: Wischmeier and Smith, 1978). The *R*-factor is a multi-annual average index that uses measures of rainfall kinetic energy and intensity to describe how rainfall

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affects sheet and rill erosion. Because also gully erosion is triggered by high-intensity rainfall (Poesen et al., 2003), we may assume that higher erosivity correlates likewise with the occurrence of more gully erosion. The standard assessment of the *R*-factor requires rain gauge recordings at short time intervals (for example 1–10 min) over multiple years. This assessment normally consists of evaluating the total kinetic energy of each storm (mostly through empirical relationships between energy and rainfall intensity) and multiplying this by the maximum rainfall intensity received during any 30-minutes of the storm. The result is the so-called EI_{30} index. Subsequently, the *R*-factor is calculated by cumulating the EI_{30} values of all storms in a year, and averaging this for multiple years (Wischmeier and Smith, 1978; Renard and Freimund, 1994). Although the USLE and its R-factor were initially designed to predict long-term average annual soil loss (Kinnell, 2010), EI_{30} may also be cumulated for shorter time-spans to assess the variability of erosivity.

The number of gauging stations that measure and report rainfall at sub-hourly intervals is limited. Africa in particular has a sparse network of gauging stations (Bastola and François, 2012). As a consequence, empirical relationships have been developed that incorporate more readily available precipitation data for mapping erosivity indices like the *R*-factor. These use for example the Fournier and modified Fournier indices that require monthly rainfall data (Fournier, 1960; Arnoldus, 1977), or direct relationships with annual rainfall (Roose, 1977). Resulting empirical relationships are however location-specific and can in most cases not be readily applied to large areas (Oliveira et al., 2013). Moreover, such empirical approaches do not utilize information on highly-variable rainfall intensities, which limits their application to the mapping of average annual erosivity.

Maps of average annual erosivity (i.e., of the *R*-factor) give a spatial overview of differences in the average potential ability of the rain to cause erosion, but do not allow to effectively describe the interaction of erosivity with other dynamic erosion-controlling factors. The USLE (Wischmeier and Smith, 1978) and its revised version RUSLE (Renard et al., 1997) address this interaction by accounting for the average "likely" annual distribution of the *R*-factor when deriving average annual soil erodibility (K) and protective crop and management (C) factors. While this annual distribution is determined for regions of the USA, many USLE applications worldwide do not account for this temporal variability aspect, which raises doubts about the validity of the resulting soil loss estimates. Besides seasonal variability, soil erosion also shows large interannual variability, for example in semi-arid tropical regions, which is linked to the variability of rainfall and vegetation cover. Despite the fact that the USLE family of models is principally intended for estimating average annual soil loss, current changes in rainfall regimes and the human impact on vegetation cover justify a closer monitoring of erosion processes and controlling factors at various scales (Poesen et al., 2003). This requires, among others, temporal information on erosivity.

Several recent studies analysed temporal changes in erosivity. Meusburger et al. (2012) used 10-minute rainfall data from 71 automatic gauging stations and regression-kriging to evaluate trends and variability in erosivity across Switzerland over a 22-year period. Longer-term trends were analysed for stations in Belgium (Verstraeten et al., 2006), Germany (Fiener et al., 2013), and Italy (Capolongo et al., 2008) from <5–20-minute rainfall data, but without spatially representing the temporal variability of erosivity. For two stations in Nigeria, Salako (2008) showed large interannual variability of erosivity examining approximately 20 yr of rain gauge data (coefficient of variation 35–40%). Huang et al. (2013) used daily rainfall from 146 gauging stations and applied an empirical erosivity model (using daily data) to spatially assess monthly erosivity trends in the Yangtze River basin in China for a 45-year period. We retrieved only two studies that use temporal information on rainfall erosivity as an input to large-scale monitoring of erosion through integration with other erosion-controlling factors. The first is by Panagos et al. (2012) who calculated monthly erosivity for a 14,500-km^2 watershed in Bulgaria and Greece. They derived detailed rainfall parameters for a single station, while monthly rainfall was the only input variable to account for the spatial variability of erosivity. These inputs were used in their own empirical formula for erosivity, and through integration with vegetation parameters derived from remote sensing monthly erosion rates were estimated. The second study models soil erosion for sub-Saharan Africa with ten-daily data on vegetation cover and rainfall (Symeonakis and Drake, 2010). The rainfall component is composed of satellite-based rainfall estimates, and number of rain-days kriged from station-data. The low number of studies in this paragraph illustrate that spatial accounting for the temporal variability of rainfall erosivity is not yet commonplace in current research aiming at effective erosion mapping and monitoring.

Satellite remote sensing can constitute an important input to soil erosion studies (Vrieling, 2006). In the absence of dense networks of gauging stations that measure rainfall at sub-daily or better sub-hourly intervals, alternative sources of rainfall data include among others ground-based radars, numerical weather prediction models, reanalysis data, and satellite-derived estimates (Tapiador et al., 2012). The relative performance of rainfall estimates from numerical models and satellites depends highly on the rainfall regime with satellites being more accurate for convective rainfall (Ebert et al., 2007). Currently, satellite-derived rainfall estimates are used frequently for a variety of hydrological applications (Kidd and Levizzani, 2011), although not yet much for soil erosion studies. For an ungauged area in Brazil, Vrieling et al. (2008) evaluated the timing of high-erosive rainfall from 3-hourly rainfall estimates derived from the Tropical Rainfall Measurement Mission (TRMM) and related this to vegetation cover development to understand when most erosion occurs. Vrieling et al. (2010) applied the 3-hourly TRMM Multi-satellite Precipitation Analysis (TMPA) data for the first time to estimate average annual erosivity (*R*-factor). This last study was conducted for the entire African continent and it was shown that the modified Fournier index applied to monthly rainfall estimates gave a better relationship with station-based *R*-factors reported in literature. Despite this last finding, we still believe that there is benefit and potential in using satellite-based short-duration rainfall intensity estimates for erosivity estimation.

The aim of this study is to evaluate the importance of the spatial and temporal variability of rainfall erosivity across Africa based on TMPA data, and to provide a way forward to account for this variability in the framework of large-scale erosion monitoring. In this study, we first revisit our previous average annual erosivity estimates for Africa (Vrieling et al., 2010) with a new version and a longer time series (1998–2012) of 3-hourly TMPA data. We then use these estimates to analyse interannual and seasonal variability of erosivity. Based on our analyses, we indicate how spatio-temporal information on erosivity may be used for erosion monitoring, and suggest how erosivity estimates may be further improved in the future.

2. Data

Existing gridded precipitation estimates that cover the African continent are based on scarce rain gauges, numerical weather prediction models (including reanalysis products), or satellite data (Tapiador et al., 2012). Of these, satellite retrievals offer the highest resolution, both in space and time. Satellite-based precipitation estimates are derived from a number of different sensors onboard satellites (Gruber and Levizzani, 2008). These include sensors that measure 1) visible and near-infrared reflection providing information on cloud properties; 2) passive microwave data that allow for the estimation of the attenuation of Earth-emitted microwave radiation caused by precipitation; and 3) active microwave data that relate backscattered radiation from precipitation to precipitation intensities (Kidd and Levizzani, 2011). To better exploit the strong points of these different types of observation, multi-sensor precipitation products have been developed. Examples of these are the TMPA products that use all of the above-mentioned sensors (Adler et al., 2000; Huffman et al., 2007). They combine microwave data from polar orbiting satellites with cloud-top brightness