Assessing the impact of climate change on soil erosion in East Africa using a convection-permitting climate model

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Abstract

East Africa is highly reliant on agriculture and has high rates of soil erosion which negatively impact agricultural yields. Climate projections suggest that rainfall intensity will increase in East Africa, which is likely to increase soil erosion. Soil erosion estimates require information on rainfall erosivity, which is calculated using sub-daily storm characteristics that are known to be biased in traditional parameterized convection climate models. Convection-permitting climate models, which are run at higher resolution to negate the need for convection parameterization, generally better represent rainfall intensity and frequency. We use a novel convection-permitting pan-Africa regional climate model (CP4A) to estimate rainfall erosivity in Tanzania and Malawi, and compare it to its parameterized counterpart (P25), to determine if there is a benefit to using convection-permitting climate models to look at rainfall erosivity. We use eight year historical and end-of-century (RCP8.5) climate simulations to examine the impact of climate change on soil erosion in Tanzania and Malawi based on rainfall erosivity estimates from CP4A and P25 applied to the Revised Universal Soil Loss Equation. The effectiveness of soil conservation measures was also evaluated. Rainfall erosivity was lower in P25 than in CP4A and was a poorer match to observational storm characteristics, even after bias-correction. These results suggest that parameterized convection regional and global climate models might under-estimate rainfall erosivity, and the associated soil erosion. We found high values of present day erosion in mountainous regions in Tanzania and Malawi in CP4A. Under climate change, areas at high risk of soil erosion expanded due to increases in rainfall intensity in CP4A. Terracing was less effective at reducing soil erosion risk in the future than in the present day, and more extensive soil management may be required to manage soil erosion and reduce the negative impacts of soil erosion on agriculture.

1. Introduction

Soil erosion is a global challenge, negatively impacting food productivity, water security and biodiversity (Panagos et al 2015b, Li and Fang 2016, Blake et al 2018). In 2012, Africa was estimated to have the highest soil erosion rates worldwide due to high rainfall erosivity and conversion of forest to crops (Borrelli et al 2017). East Africa is particularly vulnerable to soil erosion due to steep topography, fragile soils and intense rainfall (Wynants et al 2019). The high rates of present-day erosion already lead to agriculture yield reductions in the region (Lal 1995, National Economic Council Malawi 1998, Fenta et al 2019). The major factors contributing to soil erosion by water are land use, land management, rainfall, soil type and topography (Panagos et al 2015b). Climate change will impact soil erosion directly through changes in rainfall amount and intensity and indirectly through changes to land cover and decomposition rates of soil organic matter (Davidson and Janssens 2006, Biasutti and Seager 2015, Li and Fang 2016, Duulatov et al 2019). The intensity of rainfall is expected to increase in parts of East Africa.
with climate change (Shiferaw et al 2018, Kendon et al 2019), which may increase the already high rates of soil erosion (Li and Fang 2016). Despite having high rates of soil erosion there are few studies on the future impact of climate change on soil erosion in Africa (García-Ruiz et al 2015, Li and Fang 2016), and besides the global study of Borrelli et al (2020) none that we are aware of for Tanzania and Malawi. There are also limited historical or present-day soil erosion studies in Africa due to data scarcity (Vanmaercke et al 2014, García-Ruiz et al 2015, Benavidez et al 2018).

Soil erosion at the regional and global scales is commonly estimated using the Universal Soil Loss Equation (USLE, Wischmeier and Smith 1978) or its revised version (RUSLE, Renard et al 1997). RUSLE is a simple empirical model of soil erosion that requires data on rainfall erosivity, topography, soil type, land cover, and land management (Guo et al 2019). The RUSLE model was developed for sheet and rill erosion, and does not include other erosion processes such as gully erosion or landslides (Renard et al 1997). Though the RUSLE model was originally developed for the farm plot-scale using field experiments in the USA, it has been applied to many other scales and countries and is useful for identifying areas which are vulnerable to soil erosion though can struggle estimating erosion magnitudes (Benavidez et al 2018, Schüür et al 2020), including in Africa (e.g. Igwe et al 1999, Angima et al 2003, Nwaukwa and Udosen 2007, Azediji et al 2010, Maeda and Ogbi 2015). More comprehensive soil erosion models are available; however, these require additional data including, but not limited to, information on basin morphology and soil degradation (de Vente and Poens 2005). In situations of data scarcity, such as Africa, the use of soil erosion models which require these additional inputs generally increases the uncertainty in the results (Benavidez et al 2018).

In RUSLE, the rainfall impact on erosion is measured by rainfall erosivity, which is a combined measure of the amount and kinetic energy of rainfall and is ideally calculated with sub-hourly rainfall data (Wischmeier and Smith 1978). Though not all soil erosion models require information on rainfall erosivity, in general, high temporal resolution rainfall data, such as hourly or more, improves the performance of hydrological and soil erosion models, though this depends partly on the type of soil (Ficchi et al 2016, Bauwe et al 2017, Jković et al 2018, Yang et al 2020). Using RUSLE, if all other factors remain constant (topography, soil type, land cover and management), soil erosion is directly proportional to rainfall erosivity (Porto 2016). Erosion studies generally rely on station observations of rainfall (i.e. Panagos et al 2017), and climate models are not often used to calculate rainfall erosivity as it relies on rainfall intensity, which global climate models (GCMs) and even regional climate models (RCMs) struggle to represent (Dabney et al 2012). As a consequence, there are few studies on how erosion will change in the future, and those available globally (Borrelli et al 2020) and for parts of East Africa (Lankriet et al 2012, Adem et al 2016, Chimdesa et al 2019) primarily rely on annual or monthly rainfall data, and outputs from GCMs, though some also use daily rainfall and parameterized convection RCMs (Gadissa et al 2018, Jilo et al 2019). As rainfall data at the necessary temporal resolution to estimate future rainfall erosivity is not provided from parameterized convection climate models, these studies rely on assuming the relationship between aggregated climate metrics (annual, monthly, daily rainfall) and erosivity in the present day will hold in the future (Quine and van Oost 2020). Further, there are no studies that we are aware of for Tanzania and Malawi.

Convection, which is thermally driven vertical mixing of the atmosphere, is the dominant source of rainfall in many parts of the world, and is a key contributor to extreme events such as flash floods and landslides (Prein et al 2015). The convection parameterizations in GCMs and RCMs tend to produce too-frequent, light rainfall and insufficient heavy rain (Prein et al 2015). Furthermore, the rainfall intensity data from GCMs and RCMs is usually not available at a sub-hourly timestep, which leads to underestimates of the maximum 30 min rainfall intensity, and therefore rainfall erosivity (Agneze et al 2006, Dabney et al 2012, Porto 2016). The few studies that have looked at climate change impacts on rainfall erosivity have found increases in most areas, with increases in associated soil erosion or sediment yield (Biasutti and Seager 2015, Almagro et al 2017, Op de Hipt et al 2018, Amanambu et al 2019, Dvalatov et al 2019, Berberoglu et al 2020).

Novel, convection-permitting RCM simulations (CP4A) have recently become available for Africa. The convection-permitting present-day simulation has a better representation of rainfall characteristics such as rainfall occurrence, intensity, and extremes than its parameterized counterpart (Stratton et al 2018, Finney et al 2019, Kendon et al 2019, Senior et al 2021). This may make CP4A more suitable for rainfall erosivity estimates than parameterized convection GCMs and RCMs. The purpose of this study is to make use of the present-day and future convection-permitting climate simulations over Africa, to determine the benefit of improved storm representation in convection-permitting models for calculating rainfall erosivity. We then estimate water erosion in the present and future using the RUSLE model to determine the climate change impact on soil erosion. We use Tanzania and Malawi as our study area as to our knowledge, the only study on the impact of climate change on soil erosion for this region is the global study of Borrelli et al (2020), which uses monthly rainfall data
from GCMs. Further, soil erosion causes present day agricultural yield losses (National Economic Council Malawi 1998, Vrieling et al 2006), and the convection-permitting model has been evaluated extensively in this area (e.g. Finney et al 2019, 2020).

2. Methods

2.1. Climate model description

We use ten year pan-Africa regional Met Office Unified Model climate simulations, which are available for 1997–2006 for the ‘historical’ period, and 2097–2106 for the ‘RCP8.5’ future scenario (Stratton et al 2018, Kendon et al 2019). Unfortunately, some of the CP4A data for RCP8.5 from January 2097 to March 2098 was corrupted. For this reason, we have used only data from January 1999 to December 2006 for the historical scenario and January 2099 to December 2106 for the RCP8.5 future scenario.

The convection-permitting (CP4A) and the convection-parameterized (P25) configurations are both driven by a global atmosphere-only climate model simulation at 25 km horizontal resolution (MetUM Global Atmosphere 7.0, Kendon et al 2019). CP4A and P25 are regional atmosphere-only simulations, that cover the entire pan-Africa region and have a horizontal grid-spacing at the equator of 4.5 × 4.5 km for CP4A and 26 km × 39 km for P25 (Stratton et al 2018). In the historical period, both models are forced by sea surface temperatures (SSTs) from the Reynolds daily observations (Reynolds et al 2007, Kendon et al 2019). For the future climate simulations, the average SST change between 1975–2005 and 2085–2115 in the HadGEM2-ES RCP8.5 run are simulations, the average SST change between 1975–2005 from the Reynolds daily observations (Reynolds et al 2007, Kendon et al 2019). Unluckily, some of the CP4A data for RCP8.5 from January 2097 to March 2098 was corrupted. For this reason, we have used only data from January 1999 to December 2006 for the historical scenario and January 2099 to December 2106 for the RCP8.5 future scenario.

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2.2. Observational data

There are several gridded rainfall products available for the study area (figure 1) which could potentially be used for bias-correction and evaluation, however, none are available at the ideal temporal resolution of 15 min. The highest temporal resolution data available is from the Global Precipitation Measurement mission dataset, which has 30 min—hourly rainfall data available, however the timeframe of this dataset (June 2000 onwards) does not fully overlap with the timeframe of the CP4A and P25 models. The TRMM 3B42 satellite rainfall product (Huffman et al 2007) has data available at a three hourly resolution, although the spatial resolution is 0.25° × 0.25°, which if used for bias-correction of CP4A would have resulted in the loss of spatial detail. In addition, our bias-correction method is based on monthly correction factors, so would not utilize the three hourly TRMM 3B42 information. The CHIRPS v2.0 dataset (Funk et al 2015) has a higher spatial resolution of 0.05° × 0.05°, however the data is only available at daily timesteps. Therefore, we have used the CHIRPS v2.0 dataset for bias-correction, and TRMM 3B42 as an independent dataset for evaluating three hourly storm characteristics.

The TRMM 3B42 satellite rainfall product (Huffman et al 2007) combines satellite observations and rain gauges and is available from 1998 to 2014 at a three hourly timescale. CHIRPS v2.0 is a daily rainfall dataset based on satellite observations and station data and is available at a 0.05° × 0.05° resolution (approximately 5 × 5 km at the equator), from 1981 to present, though only 1999–2006 was used here to match the timeframe of the CP4A historical data. The CHIRPS dataset matches station data in Africa well for both total amount and variability of rainfall (Muthoni et al 2019). CP4A and P25 were bias-corrected to the CHIRPS v2.0 dataset using local intensity scaling (Fang et al 2015, Teutschbein and Seibert 2012; see supplementary material (available online at stacks.iop.org/ERL/16/084006/mmedia), Bias Correction). For the purposes of comparing CP4A and P25 storm characteristics, CP4A was regridded to the P25 grid (26 × 39 km).

The statistical significance of changes in storm characteristics in CP4A and P25 were evaluated using the Mann–Whitney U test.

2.3. RUSLE model

Soil erosion in the RUSLE model is calculated as:

\[
\text{Erosion rate} = R \times LS \times K \times C \times P
\]

where \( R \) = rainfall erosivity factor, \( LS \) = slope length and slope steepness factor, \( K \) = soil erodibility factor, \( C \) = cover-management factor and \( P \) = support practice factor.

The equations used in the components of RUSLE come from experiments conducted in the USA. Where possible, we have used equations for tropical soils rather than USA soils, as noted in the methods below. Given the difficulty acquiring Africa specific information, we have presented the erosion results as a map of relative risk, rather than absolute values (Benavidez et al 2018). Absolute values are presented in the supplementary material, figures S5–S6 for the purposes of comparing to other erosion studies. Categories (table 1) were chosen based on definitions of acceptable soil loss for Europe (0.3–2 t ha\(^{-1}\) yr\(^{-1}\)) and the USA (4.5–11.2 t ha\(^{-1}\) yr\(^{-1}\)) as thresholds are not available for Africa (di Stefano and Ferro 2016).

For the calculation of climate change impact on erosion, only the \( R \) factor changed between the historical and RCP8.5 scenarios. All other factors remained constant.
Table 1. Erosion values (tonnes ha\(^{-1}\) yr\(^{-1}\)) corresponding to each risk category.

| Erosion | Category  |
|---------|-----------|
| 0–2     | Very low  |
| 2.1–4.5 | Low       |
| 4.6–11.2| Moderate  |
| >11.2   | High      |

2.4. Rainfall erosivity (R) factor
We use the rainfall erosivity equation for the RUSLE model as described in Porto (2016). We have used the standard RUSLE criteria for erosive and non-erosive storms. See supplementary material, rainfall erosivity, for further details.

A component of rainfall erosivity is maximum 30 min rainfall intensity (Porto 2016). However, sub-hourly data is only available for the CP4A model and the use of hourly rainfall data has been found to underestimate the maximum 30 min intensity (Agnese et al 2006, Porto 2016). We therefore derive a simple scaling factor (SF) between rainfall erosivity calculated using 15 min and hourly data from the CP4A model and use this to estimate 30 min rainfall intensity:

\[
SF = \frac{R_{15}}{R_{60}}
\]

where \(R_{15}\) = rainfall erosivity calculated using 15 min CP4A data and \(R_{60}\) = rainfall erosivity using hourly CP4A data. SF calculated for present-day and RCP8.5 scenarios.

For consistency, we apply the SF to the hourly data from both the CP4A and P25 models, using the present day SF for the present day data and the RCP8.5 SF for the RCP8.5 data.

2.5. LS factor
The LS factor accounts for the impact of topography on soil erosion. We used the Shuttle Radar Topography Mission 1 arc-second (approx. 30 m) digital elevation model (DEM) (USGS 2000). The LS factor was calculated based on Desmet and Govers (1996) and applied using SAGA (Conrad et al 2015).

2.6. Soil erodibility (K) factor
The K factor (t ha h ha\(^{-1}\) MJ\(^{-1}\) mm\(^{-1}\)) represents the susceptibility of the soil to erosion. Input data came from the SoilGrids250m soil database, which is described in Hengl et al (2017). We used the K factor equation as described in Fenta et al (2019). See supplementary material, soil erodibility (K) factor for further details.

2.7. Cover-management (C) factor
The cover management factor accounts for how land cover and management impact soil erosion. We
estimate $C$ from MODIS NDVI data at 500 m resolution, averaged over the period 2003–2006 (Jenkerson et al. 2010). We used the following equation for $C$ from Almagro et al. (2019), which has been found to work well in tropical areas:

$$C = 0.1 \left( \frac{-NDVI + 1}{2} \right).$$

### 2.8. Support practices ($P$) factor

We use the RUSLE model with and without a support practices factor. When assuming no erosion control support practices, the $P$ factor was set to 1. When a support practice was included, we assumed terracing was used, and assigned a $P$ factor based on slope class (table 2), following the guidelines of Wischmeier and Smith (1978).

### 2.9. Land use mask

The RUSLE soil erosion results were masked outside the areas where crops are grown. To define the mask we used the 5 arc minute MIRCA2000 combined irrigated and rainfed observational dataset (Portmann et al. 2010), and excluded areas where less than 5% of the gridcell was used for growing crops. When examining yield, we used combined rainfed and irrigated maize growing areas.

### 3. Results

#### 3.1. Comparison to observations

Given the limitations in the observational datasets available, it is not possible to evaluate the 15 min or hourly model rainfall data against observations on the country scale. Instead, we compared the three hourly TRMM data with three hourly storm characteristics relevant for the calculation of rainfall erosivity (figure 2). As the bias-correction method we used corrected wet day frequency and intensity, three hourly storm characteristics in P25 and CP4A were only indirectly corrected, and so will not match exactly.

Before and after bias-correction, CP4A better represents the distribution of rainfall intensity and duration than P25 (figure 2). Before and after bias-correction, the storms in P25 have a lower average and maximum intensity than CP4A and TRMM, which means fewer storms meet the RUSLE criteria for erosive storms (see table 3). Even for storms that do meet the RUSLE criteria for being erosive, the storms in P25 have a lower maximum intensity and average intensity than in CP4A and TRMM. These results are in line with previous evaluations of P25 and CP4A, which found that P25 rains too frequently (i.e. more wet days) and rains at a lower intensity than observations (Finney et al. 2019, Kendon et al. 2019), which is a common issue in parameterized convection climate models (Prein et al. 2015).

Bias correction does not improve all attributes of storm characteristics for CP4A and P25. After bias-correction the average and maximum intensity of all storms and erosive storms in CP4A decreases (table 3, figure 2). The average and maximum storm intensity increases in P25 when all storms are considered, however there is little change for erosive storms (figure 2, panel A2 and B2). The result of these changes in storm intensity is that fewer of the CP4A and P25 storms are erosive after bias-correction and thus fewer would be included in the RUSLE rainfall erosivity calculation. This is an improvement for CP4A, which originally had too many erosive storms, but not for P25. Nevertheless, later in the paper we show that the present-day rainfall erosivity computed from CP4A after bias correction is close to that observed in previous studies. Bias correction of the hourly data required as input for the RUSLE model changes the rainfall metrics in the same way as the three hourly data (supplementary material, figure S1).

#### 3.2. Climate change impacts on rainfall

Average and maximum storm intensity increases in both CP4A and P25 in the future RCP8.5 scenario as compared to the present-day, though P25 storm intensity remains lower than in CP4A (figure 3). These results are in line with previous work, which has shown that despite similar changes in mean seasonal rainfall with climate change in P25 and CP4A, extreme (99th percentile) rainfall intensity increases by a larger amount in CP4A than P25 (Kendon et al. 2019).

The change in storm characteristics for RCP8.5 compared to the present-day is similar in the raw and bias-corrected data (figure 3, table 3). The results are similar for the hourly data (supplementary material, figure S2).

#### 3.3. Rainfall erosivity

We calculated rainfall erosivity using bias-corrected hourly P25 data and applied the CP4A historical and future SFs (see supplementary material, figures S3 and S4), and compared it to the bias-corrected CP4A hourly rainfall erosivity with SFs also applied (figure 4; for raw results, see supplementary material figure S5). The mean SF over the study area was 2.8 in the present and future.

Rainfall erosivity increases in the RCP8.5 future scenario as compared to the present-day across the entire study area, due to increases in rainfall intensity.
Figure 2. A comparison of yearly average storm intensity and maximum storm intensity in the present (1999–2006) in the raw and bias-corrected CP4A and P25 models, and the TRMM observational data. Storm characteristics calculated using three hourly data. Duration measures length of storms using a minimum inter-event time of 6 h, as per the RUSLE standard. Erosive storms refer to all storms that meet the RUSLE criteria for inclusion (total storm depth > 12.7 mm or minimum 15 min depth > 6.36 mm). All data analyzed on P25 26 × 39 km grid. As the data is an annual average, values are lower when all storms are included than when only erosive storms (which have a higher intensity) are considered.

and maximum intensity (figure 4). Bias-correction of the model output results in lower rainfall erosivity in both CP4A and P25 than in the raw data. Except in northern Tanzania using the CP4A model, the percentage change in rainfall erosivity due to climate change is similar before and after bias-correction. Even with the SF and bias-correction, rainfall erosivity in P25 is much lower than in CP4A (see table 4). The percentage increase in rainfall erosivity with climate change is higher in P25 than in CP4A, however this corresponds to a smaller absolute value.

The mean present day rainfall erosivity (\( R \) factor) calculated using CP4A bias-corrected data for Tanzania is similar here to the values found by Fenta et al (2017), which was based on satellite and station observations, at 4089 and 4340 MJ mm ha\(^{-1}\) h\(^{-1}\) yr\(^{-1}\) respectively (table 4). The Tanzania \( R \) factor calculated using bias-corrected P25 data is much lower, at 927 MJ mm ha\(^{-1}\) h\(^{-1}\) yr\(^{-1}\). Though bias-correction did not improve all rainfall characteristics for CP4A, the magnitude of rainfall erosivity in the bias-corrected data is similar to results from Fenta et al (2017), while before bias-correction it is approximately double. This improvement may be due to there being fewer erosive storms in CP4A after bias-correction, which is more in line with the
Table 3. Average characteristics of all storms in Tanzania and Malawi in raw and bias-corrected CP4A and P25 data, calculated using three hourly rainfall. Maximum intensity of three hourly storms calculated as maximum over entire storm. All storm data analyzed on P25 grid. Differences between present and future values significant at $p < 0.05$ for all variables, as evaluated using Mann–Whitney U test.

| Variable                                      | Model   | Present raw | Future raw | Future change in number of erosive storms (%) | Present bias-corr | Future bias-corr | Future change in number of erosive storms (%) bias corr |
|-----------------------------------------------|---------|-------------|------------|-----------------------------------------------|-------------------|------------------|------------------------------------------------------|
| Number of erosive storms/total number of storms | CP4     | 34/132      | 37/116     | 9                                             | 21/119            | 27/106           | 29                                                   |
|                                               | P25     | 20/201      | 27/194     | 35                                            | 17/116            | 25/120           | 47                                                   |
|                                               | TRMM    | 24/129      | —          | —                                             | —                 | —               | —                                                   |
| Average intensity (mm/hour)                   | CP4     | 1.14        | 1.56       | 37                                            | 0.91              | 1.28             | 41                                                   |
|                                               | P25     | 0.55        | 0.65       | 18                                            | 0.73              | 0.86             | 18                                                   |
|                                               | TRMM    | 1.07        | —          | —                                             | —                 | —               | —                                                   |
| Maximum intensity (mm/hour)                   | CP4     | 2.09        | 2.89       | 38                                            | 1.56              | 2.27             | 46                                                   |
|                                               | P25     | 1.01        | 1.24       | 23                                            | 1.37              | 1.70             | 24                                                   |
|                                               | TRMM    | 1.71        | —          | —                                             | —                 | —               | —                                                   |
| Duration (min)                                | CP4     | 464         | 441        | —5                                            | 431               | 420              | —3                                                  |
|                                               | P25     | 515         | 535        | 4                                            | 622               | 658              | 6                                                   |
|                                               | TRMM    | 383         | —          | —                                             | —                 | —               | —                                                   |

Table 4. Present day and future change in rainfall erosivity ($MJ \text{ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$) in raw and bias corrected CP4A and P25 data.

| Model   | Country | Present | Present bias-corrected | RCP8.5 | RCP8.5 bias-corrected | Future change (%) | Future change bias-corrected (%) |
|---------|---------|---------|------------------------|--------|-----------------------|-------------------|-------------------------------|
| CP4A    | Tanzania | 8398    | 4089                   | 15696  | 10472                 | 87                | 156                           |
|         | Malawi  | 10529   | 4325                   | 18425  | 8742                  | 75                | 102                           |
| P25     | Tanzania | 1278    | 927                    | 2602   | 2266                  | 104               | 144                           |
|         | Malawi  | 2403    | 1267                   | 4801   | 3012                  | 100               | 138                           |

TRMM data. Bias-correction improved the rainfall erosivity estimates from CP4A, and worsened the estimates from P25. This may be because the sub-daily rainfall characteristics in P25 are further from observations than the CP4A sub-daily characteristics.

3.4. RUSLE model

We use the RUSLE model using rainfall erosivity calculated using bias-corrected hourly CP4A and P25 data and applying the SFs determined from the CP4A 15 min data. The LS (slope length), $C$ (cover management), $K$ (soil erodibility) and $P$ (support practice) factors of the RUSLE model are assumed to be the same in the present and the future (supplementary material figure S6).

Erosion (figure 5) is highest in mountainous areas in the present-day and under the RCP8.5 future climate change scenario, where both the slope (LS) and the rainfall erosivity ($R$) are highest. Bias-correction mainly impacted the magnitude of overall erosion, rather than the spatial pattern (see supplementary material, figures S7 and S8).

High levels of erosion are more widespread in Tanzania and Malawi in the future than in the present day due to widespread increases in rainfall erosivity. The areas with high erosion in the future are still mainly mountainous, however the higher rainfall erosivity leads to high levels of erosion in areas with less steep slopes and lower LS factors than in the present day. Many areas with high erosion are also areas where crops are grown (figure 5). Soil erosion is higher in CP4A than in P25. In P25, moderate and high values of soil erosion are only found in RCP8.5, while in CP4A there are high values of soil erosion in the present day in mountainous areas, with and without terracing. The differences in the CP4A and P25 results are due to the higher rainfall erosivity in CP4A, and not solely due to the higher resolution of CP4A. However, when showing the erosion results on the CP4A grid, more details in mountainous areas can be resolved.

Terracing decreased the areas with high erosion in CP4A, and in the present day resulted in most mountainous areas having moderate–very low values of erosion rather than high values. In the RCP8.5 future scenario, high values of erosion are found in mountainous areas even with terracing. The impact of terracing on reducing erosion in P25 is only apparent in RCP8.5, as in the present-day erosion is low in most areas even without terracing.
Figure 3. Impact of end of century (2099–2106) climate change, RCP8.5, on storm characteristics (future–present), in raw and bias-corrected three hourly CP4A and P25 data. Duration measures length of storms using a minimum inter-event time of 6 h, as per the RUSLE standard. Erosive storms refer to all storms that meet the RUSLE criteria for inclusion (total storm depth > 12.7 mm or minimum 15 min depth > 6.36 mm). All data analyzed on P25 26 × 39 km grid.

4. Discussion

We examined the impact of climate change on rainfall erosivity in a convection-permitting climate model (CP4A) and compared the results to a parameterized convection model (P25). To our knowledge, this is the first study to look at future climate risks to erosion in a convection-permitting model, and the first study to look at future climate risks to erosion in the region. We then calculated erosion using the RUSLE model and bias-corrected CP4A and P25 data. We found large differences in the impacts of climate change on rainfall erosivity in the CP4A and P25 models, despite similar projected future changes in mean rainfall. We also found that in CP4A, climate change led to widespread increases in rainfall erosivity, and increases in erosion in areas that in the present-day are not at high-risk of erosion.

Validating RUSLE soil erosion is difficult due to a lack of soil erosion datasets, particularly in data-scarce environments such as East Africa, and because different methods of measuring soil erosion at field sites can give very different results (Benavidez et al 2018, Schürz et al 2020). While there are few observational datasets available for comparison, the results here can be compared to other erosion modeling studies for the present-day (supplementary material, figure S9). The overall erosion results from the bias-corrected CP4A are in line with previous studies in Tanzania and Malawi, which found mountain slopes were hotspots of high erosion, >10 t ha⁻¹ yr⁻¹ (Symeonakis and Drake 2010, Food
and Agriculture Organization of the United Nations 2016). Qualitatively, the high values of erosion found in the mountains here in CP4A are in line with observations from the Usambara (Kaoneka and Solberg 1994) and Uluguru Mountains (Kimaro et al 2008), the Mbeya Highlands (Mashalla 1988) and Makonde Plateau, Tanzania (Kabanza et al 2013). Our results differ from the results of Tamene and Le (2015) and Fenta et al (2019) due to differences in the land slope and rainfall erosivity factors. While the magnitude of erosion calculated using the bias-corrected CP4A data is similar in this study to the results of Fenta et al (2019), the spatial pattern differs. This is mainly due to differences in the rainfall erosivity ($R$) factor, as the other components of the RUSLE equation were calculated in a similar way with similar data-sets. The erosion results from Fenta et al (2019) were calculated using daily CHIRPS rainfall data and interpolating erosivity values reported in the literature, calculated from stations, none of which were from Tanzania (Fenta et al 2017, 2019). Without rainfall observations at the required sub-hourly temporal resolution from the required time period, it is difficult to know which $R$ factor estimates are more reliable.

There are large uncertainties involved in calculating soil erosion due to uncertainties in the input data, and because most of the equations were developed based on plot-scale experiments in the USA. Despite the limitations of the RUSLE model, it is one of the most commonly used and better performing erosion models for large-scale estimates (Borrelli et al 2017, Ferro 2010, Guo et al 2019). However, it does not perform better in all evaluations, (i.e. Tiwari et al 2000, Chandramohan et al 2015). Important limitations of the RUSLE model are that it does not include gully and stream bank erosion, wind erosion and can perform poorly in natural lands, such as forests, grassland and shrubland (Alewell et al 2019, Quine and van Oost 2020). Assessments of erosion models have found that the accuracy of input data is more of a limitation to erosion assessments than model formulation and complexity (Jetten et al 2003). Accuracy of input data is a particular issue for Africa. A lack

![Figure 4. Categories of rainfall erosivity in the historical (1999–2006), future period (RCP8.5, 2099–2106) and the percentage change, calculated using bias-corrected hourly CP4A data and P25 data. All data regridded to P25 grid.](image-url)
Figure 5. Annual soil loss by water erosion calculated with the RUSLE model using bias-corrected hourly CP4A and P25 data in present (1999–2006) and with RCP8.5 (2099–2106). Areas where MIRCA2000 dataset shows <5% of the gridcell has agriculture are masked out. LS (slope), C (cover-management) and K (soil erodibility) components the same in present day and RCP8.5 scenario. Results shown with and without terracing (P, support practice factor). Values for erosion categories based on acceptable levels of erosion in Europe (0.3–2 t ha\(^{-1}\) yr\(^{-1}\)) and the USA (4.5–11.2 t ha\(^{-1}\) yr\(^{-1}\)) as thresholds are not available for Africa (di Stefano and Ferro 2016). First row shows P4A data on 4.5 \times 4.5 km grid, second row shows CP4A on P25 grid (26 \times 39 km).

of long-term weather station records at the required temporal resolution makes estimating the \(R\) factor and SFs difficult for Africa (Fenta et al 2017). The \(K\) factor is based on soil characteristics, which are generally poorly estimated for Africa due to interpolation of sparse sampling points (Berazneva et al 2018). The accuracy of the DEM used for the LS factor is within 16 m vertically for Africa (Mukul et al 2015) and so the main limitation is in the existence of features which break up the slopes which are not captured by the DEM, such as roads, paths, fences, etc (Panagos et al 2015a). In evaluating the performance of \(C\) (cover-management) factor equations in tropical Brazilian soils, Almagro et al (2019) found the equation used here was found to give similar values as those obtained from experimental plots. The \(P\) factor (support practice) is the most uncertain factor in RUSLE, and should be viewed here as an example of how land management may be helpful in reducing erosion (Xiong et al 2019). Given the limitations in the input data and the RUSLE model the high erosion areas found here should be considered areas of concern for further study and management.

The magnitude of rainfall erosivity differed in P25 and CP4A, even after bias-correction, while the spatial pattern was similar. After bias-correction the magnitude of rainfall erosivity values from CP4A were in line with previous work (Fenta et al 2017), while those of P25 were much lower. This may be due to the sub-daily characteristics of rainfall in P25, which were not corrected by our bias-correction method, differing from observations and CP4A. This resulted in CP4A having hotspots of high erosion in
the present day and future, while erosion was low in most areas in the P25 model. The absolute change in rainfall erosivity with climate change in P25 was also much lower than in CP4A. Given rainfall erosivity is much lower in P25 than in other estimates for the region, the erosion results are likely to be underestimated when using P25 data. The climate change signal may also be under-estimated. Other parameterized convection GCMs and RCMs have the same problems with rainfall frequency and intensity as the P25 model (Prein et al 2015). Indeed, the rainfall erosivity results from CP4A were also very different to the results from Borrelli et al (2020), which found decreases in future rainfall erosivity when using monthly rainfall from GCMs to calculate rainfall erosivity. Even though total rainfall decreases in some parts of Tanzania in CP4A with climate change (Finney et al 2020), rainfall erosivity increased everywhere, due to increases in sub-daily rainfall intensity. This is not something that would be captured using monthly data from a GCM. Given the large differences between P25 and observations, even after bias-correction, and the differences between P25 and the convection-permitting CP4A, parameterized models may not be appropriate for applications which require information on rainfall frequency and intensity on the sub-daily scale (erosion, flash flooding, rainfall extremes) and may result in large under-estimates of these values in the present day, and under-estimates of the climate change signal.

The CP4A RCP8.5 results are not a prediction of future rainfall erosivity, but can help us gain an understanding of potential future changes in erosivity and the associated erosion relative to model baselines. We found widespread increases in rainfall erosivity in the future climate scenario as compared to the present-day, due to increases in rainfall intensity in the CP4A and P25 models. This led to an increase in areas in Tanzania and Malawi at risk of high erosion in the CP4A model. High levels of erosion were still mainly limited to mountainous areas in the future, however areas with shallower slopes became at risk of erosion when they may not be in the present-day. Many areas where erosion increased are also areas where crops are currently grown (according to the MIRCA2000 dataset). The threshold we used for high erosion is at the upper limit of acceptable soil erosion in the USA, and double the limit of acceptable soil erosion for Europe (di Stefano and Ferro 2016), and so while it is difficult to say how much agricultural yields will be impacted, it is likely that erosion in this category will lead to reduced agricultural yields. Terracing reduced the size of high erosion areas in the present day in CP4A, however, with climate change, erosion remained high in some areas even with terracing. These results show negative agricultural impacts of soil erosion may increase in already at risk areas, and spread to areas that are not currently experiencing high levels of soil erosion, and that in areas where soil conservation measures are effective, they may not be effective in the future.

Data availability statement
The data that support the findings of this study are available upon reasonable request from the authors.

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