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ORIGINAL ARTICLE

Spatio-temporal analysis of rainfall variability and seasonality in Malawi

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Abstract

Food security in Malawi relies on rainfall amount and timing. Because agricultural production is the main source of income for most rural communities, increased frequency of extreme events will increase the risk of production failure—a major threat to food security. Evidence of changing rainfall is reported by farmers and by recent analysis of gauge measurements, but these studies are limited due to small sample size, type of tests, or both. The main goal of this study is to test both statistically significant and robust but less significant changes in rainfall and rainy season for 1981–2018 using a high-resolution gridded dataset (0.05°). We analyzed different indices including onset, length, and cessation of rainy season, number of dry days, and number of extreme events during the rainy season. Our results show that roughly one-third of Malawi has experienced at least one type of significant change in rainfall indices during the study period. For instance, Northern Malawi had ~2 fewer extreme event days/decade and an end of season ~5 days/decade earlier as well as ~5 fewer dry days/decade. For the entire time period, delayed onset varies spatially from 18 to 35 days, number of dry days has decreased 21.6 days, the rainy season has ended 28.8 days earlier in the north and 36 days earlier in the south, and the number of extreme events has decreased 5 to 7 days in many places. The results are heterogeneous spatially and suggest that broad scale forcings are not driving them.

Keywords Malawi · Rainfall variability · Onset · Cessation · Rainy season · Extreme events · Dry days

Introduction

Temporal and spatial variability of rainfall is a key factor in water resources planning and management, agriculture planning, flood frequency analysis, and hydrological modeling (Michaelides et al. 2009). Food security risk is persistent in southern Africa (Williams and Funk 2011) and relies on rainfall amount and timing. This risk stems from several interconnected factors ranging from biophysical limitations to political and socioeconomic conditions. Malawi, in Southern Africa, is among the world's twelve most vulnerable countries to the adverse effects of climate change (The World Bank 2010), and farmers are affected directly by climate-related stressors such as floods, droughts, and dry spells (Chinsinga 2011). Because agricultural production is the main source of income for most rural communities, increased frequency of extreme events will increase the risk of production failure—a major threat to food security (Asfaw et al. 2015). Adaptation strategies are limited: Malawi has used a variety of approaches to boost food security including the Farm Input Subsidy Programme (Messina et al. 2017) and via efforts to manage land tenure. Irrigation as an adaptation covers only 2.3% of

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farms (Raney 2005) and is expensive to implement. About four-fifths of Malawians rely on maize as a staple food (FAO 2009). So, food security research for Malawi has thus focused on adapting planting times. Planting is initiated by the Onset of the Rainy Season (ORS). The End of the Rainy Season (ERS) and the Length of Rainy Season (LRS) are also meaningful predictors of yield and food security (Maitima et al. 2009).

Effective estimates for ORS and LRS are vital for setting planting time (Snapp and Pound 2017). Any changes in rainfall amounts, intensity, or temporal or spatial distribution would further threaten food security (Barron et al. 2003; Maitima et al. 2009). For example, by the end of 2015 farming season, delayed onset between 10 to 50 days dramatically reduced yield. Excessive rainfall/flooding after planting leads to reduced harvests (MacColl 1990). The failure of consecutive rainy seasons in East Africa associated with El Niño in 2017 impacted approximately 6.7 million people in Malawi (FEWSNET 2017). Understanding rainfall variability and its predictability is important for farmers, policymakers, and hydrologists.

What is known, and what is poorly understood, about Malawi's rainfall changes? Research gaps in rainfall studies, especially in less developed countries, are hampered by a lack of high-quality observed climate data in terms of spatial resolution, absence of research attention, and political barriers (Desa and Niemczynowicz 1996; Alemaw and Chaoka 2002; Shongwe et al. 2006; Sawunyama and Hughes 2008; Kizza et al. 2009; Ngongondo et al. 2011). These factors motivate a deeper, multiple dataset investigation on changes and trends of rainfall characteristics.

Various factors hamper study of changing rainfall characteristics. Research on rainfall tends to focus on predictability; trends in drought are evident but causality and shifts in synoptic-scale factors remain poorly understood (Nicholson 2017). Rainfall in Malawi is driven by the north-south passage of the ITCZ (Intertropical Convergence Zone) together with influences from the Congo air boundary, bringing a rainy season that runs from November to April. ENSO (El Nino Southern Oscillation) is another synoptic-scale factor that affects Malawi's rainfall variability. Several studies have explored drivers of changes in Malawi's climate seasonality. Nash et al. (2018) looked at the nineteenth-century rainfall data and found significant but complex changes in wet and dry seasons associated with El Nino conditions. Kumbuyo et al. (2014) also suggested evidence for seasonality to be affected by the quasi-biennial oscillation (QBO). Dunning et al. (2016) similarly found large shifts in the rainy season coincident with El Nino years in East Africa. Vrieling et al. (2013) reported a reduction in the length of growing period for Malawi over 1981–2011 using NDVI (Normalized Difference Vegetation Index). However, these are not associated with specific climate trends.

Previous studies have investigated rainfall variability and trends across Malawi. Nicholson et al. (2014) analyzed mean rainfall climatology and interannual variability with ORS, ERS, and LRS and found two patterns: first, a strong rainfall maximum on Lake Malawi's western shoreline during boreal spring and second, a reduced rainfall pattern in mid-February which are attributed to coarse-scale circulation changes. Vincent et al. (2017) showed a broad drying trend in annual rainfall across Malawi since 2000, lacking statistical significance due to high variability. Ngongondo et al. (2014; hereafter, NTX14), the study closest to this one, analyzed extreme indices to detect rainfall onset, length, and cessation of growing season at 26 stations in Malawi from 1961 to 2009. The results show a country-wide shift in ORS and ERS, but without significant changes at the $\alpha = 0.05$ level in length of the growing season.

However, farmers report changes in rainfall. Increased dry spells are strongly associated with drought and may be related to broader climate changes in Southern Africa (Frich et al. 2002; Nastos and Zerefos 2009; Bouagila and Sushama 2013). This suggests that characterizing the effects of climate change on rainfall for much of Africa may not be evident in a single variable (e.g., average annual rainfall) and may not be captured due to low station density. Gridded datasets may be better at detecting these changes being reported anecdotally.

What do farmers observe? Simelton et al. (2013) used farmer's perception of rainfall change in Southern Malawi and Botswana and compared them with meteorological data to address whether rainfall has changed. They found mismatches between farmers' perceptions and meteorological data. Some farmers noted higher interannual variability in the timing of the onset while others reported that the rainy season had started earlier and ended later. However, weather data proved otherwise (Sutcliffe et al. 2016). Anecdotal evidence can be misleading. Fisher et al. (2010) found discrepancies between farmers' perception of rainfall variability and climate statistics using personal interviews. Joshua et al. (2016) found that farmers' perception of climate change in Mphampha, Malawi, included more variable rainfall with a later onset and earlier cessation, plus midseason dry spells. Reports further south in Bolero describe warmer temperatures and less rainfall during the past 10 years while the climate data showed significantly increasing temperatures but an insignificant decreasing trend in rainfall (Munthali et al. 2016). Climate models project a shorter growing season (by 20–55 days) by midcentury, associated with an earlier end date, but with no significant change in onset (Vizy et al. 2015). At best, the evidence is equivocal for a shift in rainfall, yet climate model projections suggest significant changes are underway or imminent (IPCC: Niang et al. 2014). For these reasons, and for more spatially extensive coverage, we tested for statistically significant spatial and temporal changes in rainfall from 1981 to 2018 across Malawi.

The big picture question is "how is climate change affecting agriculture in the developing world?" To answer this, we chose a gridded dataset validated against gauge precipitation measurements at available geographic locations. Our null hypothesis is "there have been no significant changes in different rainfall indices over Malawi temporally and spatially." We used the non-parametric Mann-Kendall test to determine the spatiotemporal direction and magnitude of changes in rainfall behavior. To assess the spatial distributions of these various changes, we produced a zoning map which aggregated all significant changes of the precipitation variability indices across Malawi.

Data and methodology

Study area

Malawi is one of the "Feed the Future" countries for USAID (United States Agency for International Development) in Southeast Africa (Jury and Mwafulirwa 2002). The total area of Malawi is about 118,484 km^2, which is divided into lands and water bodies including Lake Malawi in the east (Fig. 1). The Great Rift Valley dominates topography in the region from north to south. The mild tropical climate has an austral summer rainy season, while the winter is very dry (Jury and Mwafulirwa 2002). Variations in climate would adversely affect most farmers (CDIAC cited in UNDP 2007). Malawi is vulnerable to drought as rain-fed agriculture covers 40% of their domestic product and with three-fifths of the population under the poverty line (Mukherjee and Benson 2003; Devereux et al. 2006). Understanding shifts in variability and changes in rainfall is essential at finer scales for adequate planning.

Data

Of the 43 weather stations available across Malawi, we chose observations that had records from 1982 onward. Seventeen of these datasets were omitted because their observations did not extend into the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) period, which started in 1982. This yielded only 26 stations that had more than 4 years during the 1982–2018 time period. These 26 stations were used to validate gridded CHIRPS data. Figure 2 shows the geographical location and spatial distribution of the stations.

We required a gridded dataset with both fine spatial (less than 50 km) and temporal (pentad or finer) resolution. Gauge measurements are not spatially representative of Malawi's climate or topography and almost all gridded rainfall datasets are either at a daily frequency or high spatial resolution, but not both. For this reason, we chose to examine CHIRP, CHIRPS, ARC2, and PERSIANN-CDR gridded rainfall products to compare the results and to find the best available gridded dataset for analysis.

CHIRPS is a global expanded rainfall gridded dataset, with a spatial resolution of 0.05° and a daily time scale. This dataset is based on thermal infrared rainfall products including the National Oceanic and Atmospheric Administration (NOAA)'s rainfall estimates, ARC2 (African Rainfall Climatology), the University of Reading's TAMSAT African Rainfall Climatology and Time series (TARCAT), and the Tropical Rainfall Measuring Mission Multi-satellite Rainfall Analysis version 7 (TRMM 3B42 v7) (Funk et al. 2015). CHIRPS shows lower bias than the other gridded products (Funk et al. 2015). There are limits to using CHIRPS; however, given the very limited gauge measurements across Malawi, and no other fine resolution gridded datasets over Eastern Africa, this was the best available dataset in terms of temporal and spatial resolution, and analysis and resampling algorithms.

ARC2 with 0.1° spatial resolution provides more than 30 years of rainfall estimates. Mean spatial distribution, annual cycle, and interannual variability of rainfall in ARC2 shows consistency with GPCP (Global Precipitation Climatology Project) and PREC/L (NOAA's PRECipitation REConstruction over Land) long-term monthly rainfall datasets. The monthly validation shows agreement with weather gauge measurements in central and southern Malawi, with a tendency to underestimate rainfall amounts. ARC2 has been used to analyze wet and dry spells, onset, peak, and extreme events across Africa (Novella and Thiaw 2012).

PERSIANN-CDR (The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks—Climate Data Record) provides a 30-year record of daily rainfall at 0.25° spatial resolution. This product is suitable for global climate studies at the scale of extreme weather events (Ashouri et al. 2015), although it tends to overestimate rainfall compared to the other rainfall products (Sun et al. 2018). All rainfall products show general underestimation of heavy rainfall over East Africa compared to gauge observations from 205 stations (Thiemig et al. 2012).

CHIRP (Climate Hazard Group InfraRed Precipitation) is developed based on global 0.05° monthly rainfall climatology (CHPclim: The Climate Hazard Group's Precipitation Climatology version 1). The only difference between CHIRP and CHIRPS is that CHIRP relies solely on remotely sensed observations and is captured as pentads. Daily values are disaggregated pentads based on daily CFS (Climate Forecast System) fields rescaled to 0.05° resolution (Funk et al. 2015). This disaggregation assumes that the total rainfall over the pentad is distributed randomly over the 5-day window and is a significant source of uncertainty that CHIRPS seeks to remediate; thus, the uncertainty in CHIRP is higher where stations are sparse.

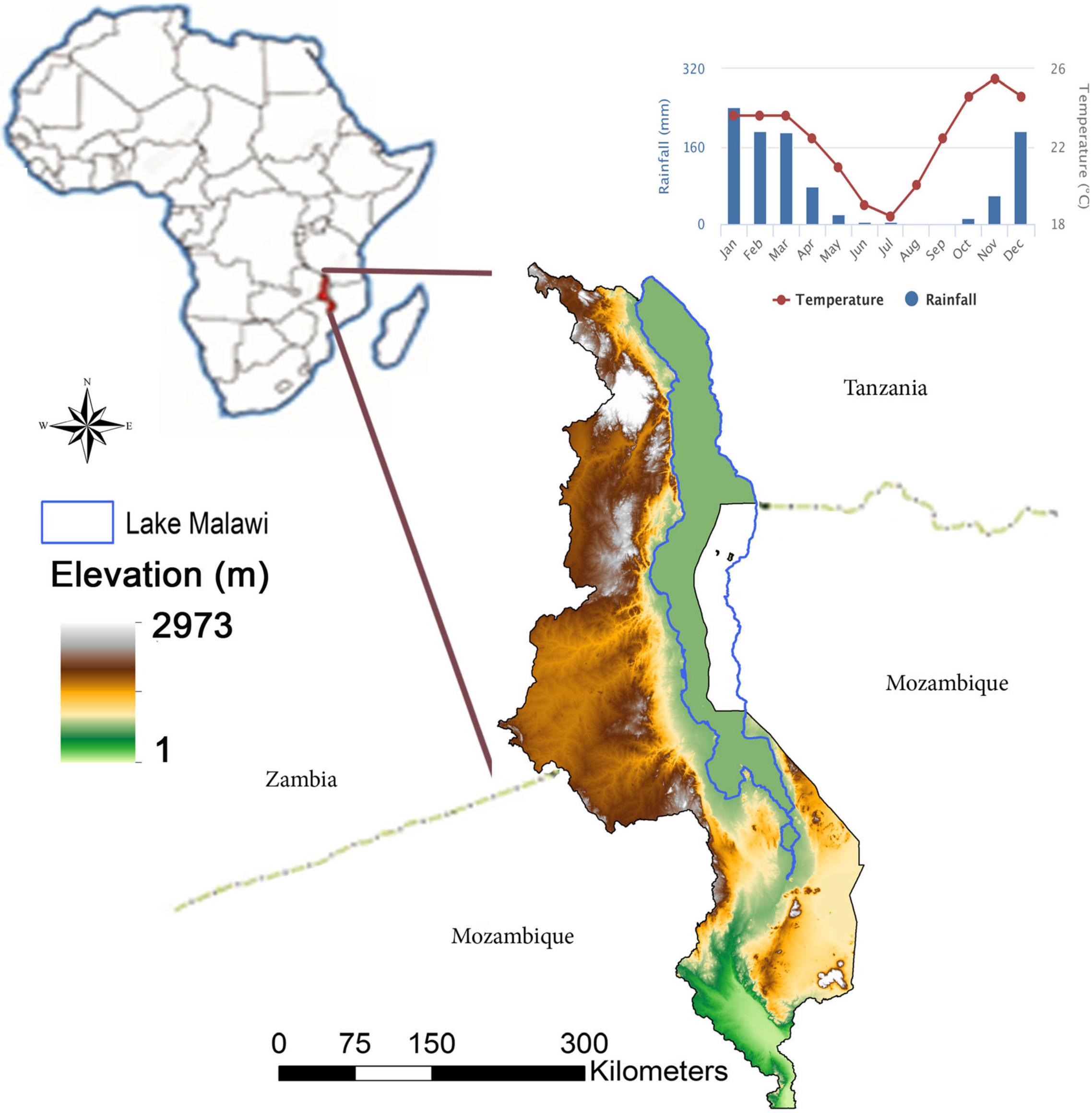

Fig. 1 Geographical location of Malawi with annual monthly rainfall and temperature distribution on the upper right

Methodology

Gridded dataset accuracy assessment

To assess CHIRPS accuracy and consistency, we compared daily gauge measurements from NTX14 with corresponding CHIRPS values (1981–2018) at the same location as the stations using a 2-mm buffer (Eq. 1). Cross-validation and correlation were applied to assess agreement during October through March. We only used rainy season data to minimize the effect of dry days within the dry season. To calculate correlation between daily rainfall of CHIRPS and gauge data, we tested a variety of pixels. Using a single pixel produces a different correlation than multiple pixels and merely show a change in correlation due to aspects of resolution. Thus, we tested one pixel, five-pixel (center plus four), and nine-pixel (3×3) resolutions against the gauge measurements. We found similar correlation values and report the single pixel results.

$$\text{IF [CHIRPS}-\text{STATION]} <= 2\ \text{mm/day, then 1, otherwise 0} \tag{1}$$

We calculated "similarity" and "correlation" to understand the degree of alignment. "Similarity" shows the amount of agreement between station value and CHIRPS value based on daily rainfall comparison. The "correlation" value is the Pearson correlation coefficient. The Sen's slope estimator of daily rainfall for the gauge measurements, CHIRPS and PERSIANN, are also shown in the online resource 1 for comparison.

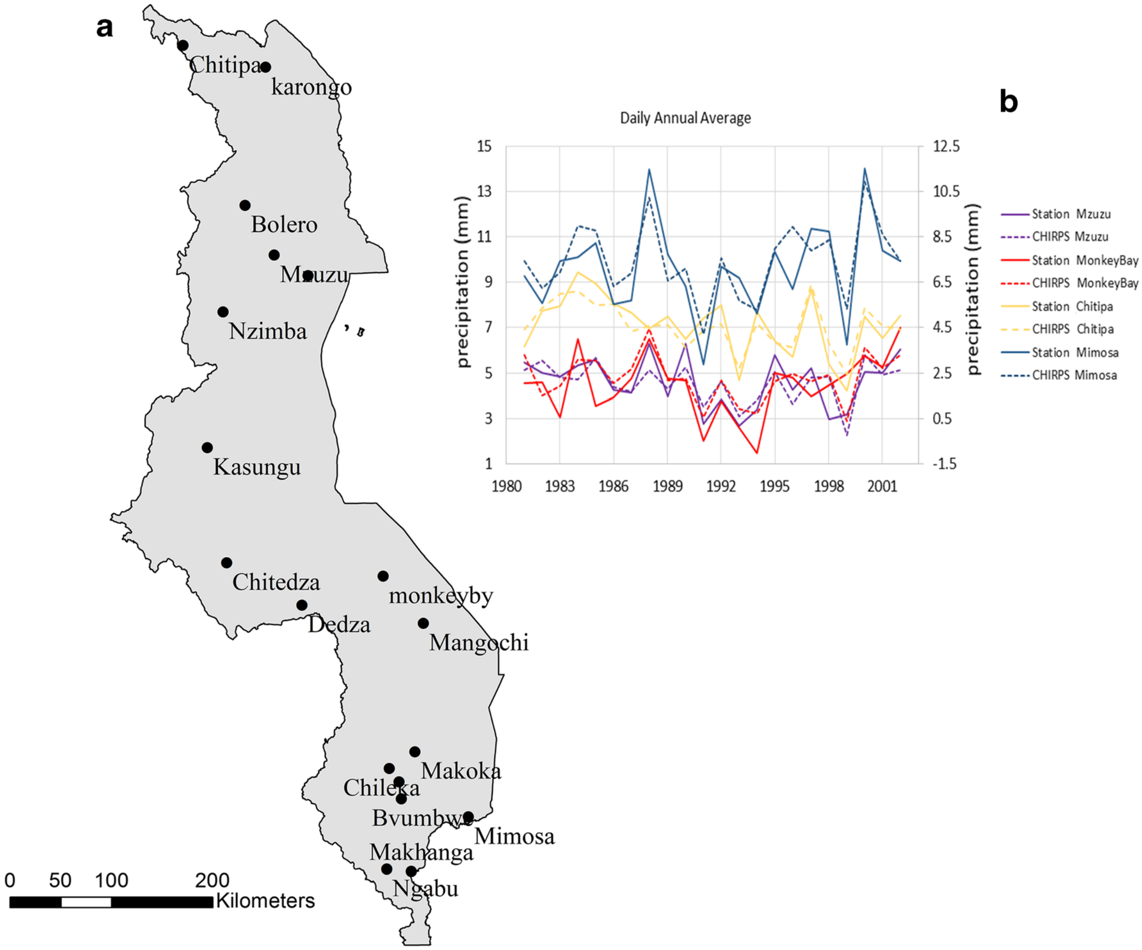

Fig. 2 CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) validation; a weather stations spatial distribution, b daily annual average of rainfall for selected stations, Chitipa, Mzuzu, Monkey Bay, and Mimosa and corresponding gridded dataset value

Rainfall variability

We developed several indices to capture rainfall variability, which include ORS, ERS, LRS, NXE (number of extreme events), and NDD (number of dry days) (Table 1) using Python version 2.7.5. Several definitions of ORS have been tested in the literature (FAO 1986; AGRHYMET 1996; Omotosho et al. 2000; Camberlin and Diop 2003; Raes et al. 2004; Tadross et al. 2009; Liebmann et al. 2012; Fiwa et al. 2014; NTX14). However, finding the best method is difficult since algorithms are not defined along with the same scales, and estimation of the "start" is somewhat subjective. We defined ORS as "a day after October 1st when the accumulated rainfall in 5 consecutive days exceeds 5 mm, followed by 10 mm in the next 10 days", based on the Famine Early Warning System given by AGRHYMET (1996). The end date of the rainy season was determined by simply reversing this process, except with rainfall amounts falling below the 5 mm threshold. Dry days and extreme rainfall are calculated following

Table 1 Definition of rainy season indices

Indices	Definition
ORS (Onset of Rainy Season)	Any day after October 1st with accumulated rainfall in 5 consecutive day more than 5 mm following by 10 mm accumulated rainfall in the next 10 consecutive days.
ERS (End of Rainy Season)	Any day after February 1st with cumulative rainfall in 10 days less than 20 mm, and following with less than 10 mm rainfall in the next consecutive days.
LRS (Length of Rainy Season)	Days between start and end of rainy season.
NXE (Number of Extreme Events)	Number of days with more than 20 mm rainfall. (> 20 mm)
NDD (Number of Dry Days)	Number of days with less than 2 mm rainfall during the rainy season. (< 2 mm)

Tadross et al. (2009) and Nicholson et al. (2014). An "extreme event" day (NXE) is defined as a day with the rainfall of more than 20 mm (> 20 mm) and a dry day is a day with less than 2 mm during the rainy season (< 2 mm). Length of rainy season (LRS) is the number of days between ORS and ERS (ORS − ERS). As a result, we made 5 different gridded maps that show spatial and temporal distributions of each metric for Malawi.

Statistical approach

Statistical analyses were done using R statistical software (version 1.1.477). Pixel by pixel analysis identified the spatial distributions of the trends. We used two non-parametric methods to identify the strength and magnitude of the trends because the data were not normally distributed, and non-parametric tests are less sensitive to outliers. The widely adopted Mann-Kendall test was used to analyze trends in climate and hydrology data (e.g., Wilks 2011; Zilli et al. 2017; Sharma and Singh 2019). The non-parametric Mann-Kendall test examines the distribution of data to be independent and identical. The main reason for using a non-parametric test is that non-parametric tests are suitable when there is missing data in time series, the distribution is non-normal, or the data set is censored (Boslaugh 2012). The null hypothesis is that there is no trend (Mann 1945; Kendall 1970), while our hypothesis states that there is a monotonic trend over time.

We calculated the test statistic Tau using the "Kendall" package (McLeod 2011) in R. The range of Tau is between − 1 to + 1, with negative values showing a decreasing trend (more negative "steps") and positive values showing an increase in trend (more upward "steps"). A significance level of $\alpha = 0.05$ was used in this study to identify significant trends.

To quantify the trend magnitude for all five indices, the Mann-Kendall test has been widely used with the non-parametric and robust Sen's slope estimator (Xu et al. 2003; Partal and Kahya 2006; Gocic and Trajkovic 2013; Sharma and Babel 2014; Wu et al. 2014) as the distributions may deviate significantly from a Gaussian distribution. This test is also not highly sensitive to skewness or large outliers (Kumar Sen 1968). Details on Sen's slope estimator and the Mann-Kendall test are described in Yue and Pilon (2011).

Results

Gridded data validation

CHIRPS vs. gauge measurements

Figure 2 and table 2 shows a 60% correlation between gauge measurements and corresponding CHIRPS daily values.

Table 2 Correlation and similarity (within 2 mm agreement) between station data and CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) at a daily frequency

Station	Longitude (degree, W)	Latitude (degree, S)	Altitude (m)	Correlation	Similarity (%)
Bolero	33.78	11.02	1100	0.62	57.55
Chitedza	33.63	13.97	1149	0.67	53.83
Makhanga	35.15	16.52	76	0.73	68.60
Monkey Bay	34.92	14.08	482	0.72	58.99
Nkhata Bay	34.30	11.60	51.91	0.61	58.99
Bvumbwe	35.07	15.92	1146	0.86	57.50
Chichiri	35.05	15.78	1132	0.74	56.51
Chileka	34.97	15.67	767	0.90	58.77
Chitipa	33.27	9.70	1285	0.91	53.35
Dedza	34.25	14.32	1632	0.70	53.30
Karongo	33.95	9.88	529	0.84	54.84
Kasungu	33.47	13.02	1058	0.77	59.22
Makoka	35.18	15.53	1029	0.87	58.64
Mangochi	35.25	14.47	482	0.72	60.78
Mimosa	35.62	16.07	652	0.88	52.66
Nzimba	33.60	11.90	1349	0.72	53.43
Mzuzu	34.02	11.43	1254	0.75	52.91
Ngabu	34.95	16.50	102	0.89	66.82

Many stations were used in building CHIRPS, so as expected, we found a strong agreement. For example, looking at Nkhata Bay station in Northern Malawi, the correlation between gauge measurements and CHIRPS values was 0.61. Even higher, Mangochi station had a correlation coefficient of 0.72. Based on these correlations and all other station correlations and similarities, CHIRPS data are the most reliable of the available datasets to use for change detection and significant trend analysis.

To have a better comparison of gridded data and gauge measurements, we produced a map of Sen's slope of ORS and ERS using stations, PERSIANN, and CHIRPS, which is available in the appendix. Based on this map, CHIRPS shows the highest agreement with gauge measurement trends. Although the values do not match perfectly, the trend shows agreement on whether it is increasing or decreasing.

CHIRPS vs. other gridded data

We applied the Mann-Kendall test (reporting Tau for our first step) on all 4 gridded datasets to compare the spatial pattern of trend in all 5 indices. Results are shown in Fig. 3.

Figure 3 compares datasets spatially, and we did not calculate significance; this is done in the section on Sen's slope below. Figure 3a shows the Mann-Kendall trend of ORS over all datasets. There is an overall agreement between CHIRPS, ARC2, and PERSIANN especially in south Malawi of 0.1 days/year, or a delay of 10 days/decade in onset. In Northern Malawi, PERSIANN and ARC2 show a retreating trend (earlier onset) of ~ 1 day/decade. PERSIANN captures the positive trend in the Southern Malawi in agreement with CHIRPS. Central Malawi shows a delay in onset trend of between 1 and 2.5 days per decade. There is broad agreement between different datasets in terms of onset of season except for CHIRP, which shows very few strong trends. In Fig. 3b (number of extreme events), there is general consistency between CHIRPS, CHIRP, and ARC2 except in Northern Malawi, where the inclusion of gauge measurements in CHIRPS shows a decrease in NXE. The decrease in Northern Malawi is also shown in the station's analysis from NTX14. PERSIANN disagrees with the first three datasets and shows a dissimilar trend and pattern. Despite annual average rainfall showing a statistically significant increasing trend from 1901 to 2018 over Eastern and Southern Africa, PERSIANN overestimates the amount of rainfall in Malawi compared to the other datasets and is coarser in resolution. This is the main disagreement between PERSIANN and other datasets.

Figure 3c shows ERS across the entire region. CHIRPS and CHIRP show sharply differing trends in Central and Northern Malawi, and PERSIANN and ARC2 are mostly homogeneous. The change in ERS in Northern Malawi based on CHIRPS and CHIRP is roughly 0.4 days earlier per year or a rate of 4 days/decade. While CHIRPS and CHIRP show earlier cessation, PERSIANN and ARC2 show later cessation. Patterns in ERS are similar to patterns in NXE for ARC2 and PERSIANN, suggesting that extreme events may need to be examined in connection to drivers of cessation.

Figure 3d shows the trend in number of dry days (NDD). In the South and Central Malawi, all gridded datasets show a similar positive trend—1 to 3 more dry days per decade. As the spatial resolution becomes coarser, the trend is larger. CHIRPS shows the mildest change in NDD, and along with CHIRP indicates fewer dry days in northern Malawi.

Interannual rainfall trends

Because of general similarity, higher resolution, the inclusion of gauge measurements, and the highest agreement with station trends, we focused on CHIRPS for the next step. Similar to Dunning et al. (2016), ORS and ERS trends show shorter and weaker rainy seasons nationwide. Figure 4 shows the non-parametric Sen's slope of the trend at the 5% significance level for all 5 indices. Many of the variables have connected trends.

Starting with ORS, at the 95% confidence level, there are two significant areas of changes in the south and along the lake. In the southern part around Bangula, the rainy season has become delayed ~ 34.5 days since 1981, and in the areas along the lake close to Salima and Mkaika, the rainy season has been delayed ~ 18 days. The shift in onset has occurred mainly in more recent years.

Number of dry days (NDD) during the rainy season has been decreasing from 1981 to 2018 in Northeast Malawi which is the wettest part of Malawi. Thus, NDD tends to be fewer in recent years with essentially no trend in NDD for most of the nation. Region from Kaporo and Mwenitete to Kaonga has experienced lower NDD, about 21.6 days in 2018 compared to 1981. The rest of the significant changes has happened over the lake in Northeastern Malawi. This is a strong decline. The minimum amount of significant decrease is about 7 days for this region.

There is a large contiguous area of significant changes in ERS over Malawi in the north. This trend is uniformly negative (i.e., earlier end of rains) at the 5% significance level as the season tends to end earlier. In Fig. 4, areas around Chitipa, Misuko, and Kameme in the north, Livingstonia in northeast and Chikangawa in the center of Malawi has experienced earlier ERS about 28.8 days in the north and center and 21.6 days earlier in the northeast. These results are broadly consistent with NTX14, but this method shows how change is spatially distributed. In the south, around Mbenje and Lujeri, the rainy season has ended 36 days earlier than it was in 1981.

NXE shows a negative trend that is spatially similar to ERS—evident in the other datasets as well. Within a 5% significance level, the Sen's slope shows a declining trend of the number of extreme rainfall days. This pattern covers nearly all northern Malawi and is spottier over southern Malawi. In the

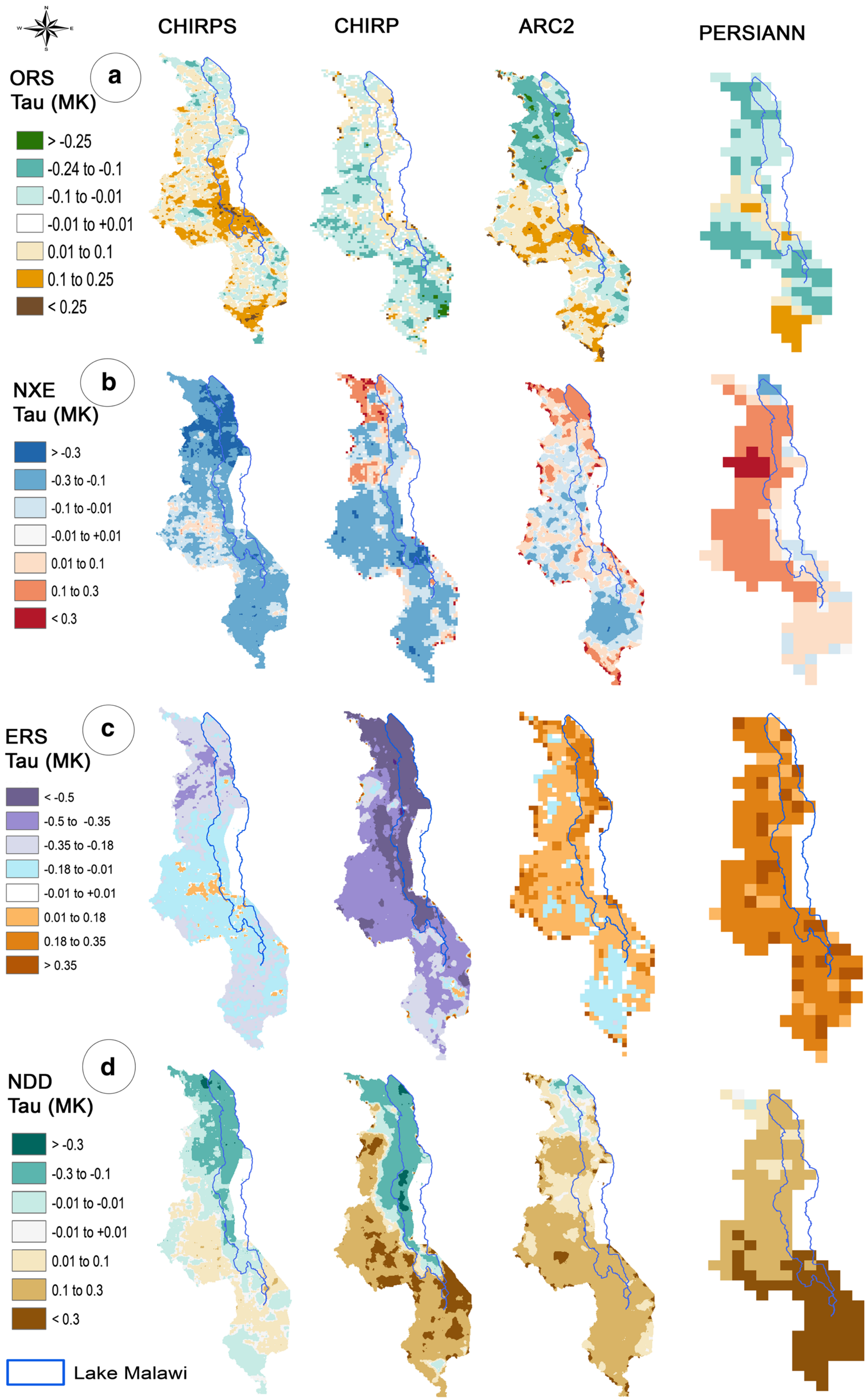
CHIRPS
CHIRP
ARC2
PERSIANN
a
ORS
Tau (MK)
> -0.25
-0.24 to -0.1
-0.1 to -0.01
-0.01 to +0.01
0.01 to 0.1
0.1 to 0.25
< 0.25
b
NXE
Tau (MK)
> -0.3
-0.3 to -0.1
-0.1 to -0.01
-0.01 to +0.01
0.01 to 0.1
0.1 to 0.3
< 0.3
c
ERS
Tau (MK)
< -0.5
-0.5 to -0.35
-0.35 to -0.18
-0.18 to -0.01
-0.01 to +0.01
0.01 to 0.18
0.18 to 0.35
> 0.35
d
NDD
Tau (MK)
> -0.3
-0.3 to -0.1
-0.01 to -0.01
-0.01 to +0.01
0.01 to 0.1
0.1 to 0.3
< 0.3
Lake Malawi

Fig. 3 Comparison of the spatial pattern of trend by Tau values using 4 different gridded dataset, CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data), CHIRP (Climate Hazard Group InfraRed Precipitation), ARC2 (African Rainfall Climatology version2), and PERSIANN (The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) for **a** Onset of Rainy Season (ORS), **b** Number of eXtreme Events (NXE); **c** End of Rainy Season (ERS); and **d** Number of Dry Days (NDD)

northwest, areas around Chilumba, NXE has decreased ~ 5.4 days over 36 years. In the north, around Kopa Kopa and Kapirinkonde, it has decreased ~ 7 days over 36 years. In the south, around Tedzani, another significant decline in NXE about 7 days over 36 years is highlighted. These small trends in such a highly variable system can be significant if the region already has a very low instance of extreme events.

The LRS trend map displays very few significant changes in the LRS mostly in the south. According to Figure 4, in the south, around Sandama, the rainy season has shortened by 75.6 days over 36 years, while in Bangula it has shortened by 54 days over the time span examined. Although there are a few pixels scattered in the center and south of Malawi with a positive trend. In these areas, the rainy season has been lengthened to about 49.3 days over 36 years.

Discussion

Broad trends and variability

Comparing CHIRPS to gauge measurements and three other gridded datasets helped us to understand if CHIRPS is consistent and if the gridded datasets broadly agree. We found that the higher spatial resolution datasets gave more consistent results. As previously noted, reanalysis datasets show a higher variability compared to gauge-based and satellite-based datasets (Sun et al. 2018). PERSIANN-CDR (0.25° resolution) was unable to capture much of the variability of indices found with the others. It overestimated rainfall amounts and was inconsistent with the NXE gauge measurements compared to the consistent trend among the other three (CHIRPS, CHIRP, and ARC2). Trends in other indices such as ORS, NDD, and ERS showed a similar pattern; as pixel size reduced, variability increased. Fidelity to gauge measurements is important, as gauge measurements remain the gold standard. However, in the absence of gauge measurements, it was difficult to discriminate which stations were accurate.

The null hypothesis posits no significant changes in different rainfall indices. However, anecdotal reports motivated a second look at these and other trends. Several studies have found weak trends or statistical insignificance in the ORS, ERS, LRS, and NXE, but limited to only gauge measurements. Others (e.g., Tadross et al. 2009; Dunning et al. 2016) were continental in scale and not easily downscaled/granular enough to look at Malawi specifically. Our results broadly echoed the reported mismatch between meteorological data and farmer's perceptions of trends (Simelton et al. 2013). These results show that much of Malawi is indeed experiencing some statistically significant changes in how the rainy season behaves. NTX14 lacked the spatial extent of gridded data needed to identify significant changes at the $\alpha = 0.05$ level for ORS, ERS, and LRS in under-measured locations. This study partly resolves this apparent discrepancy.

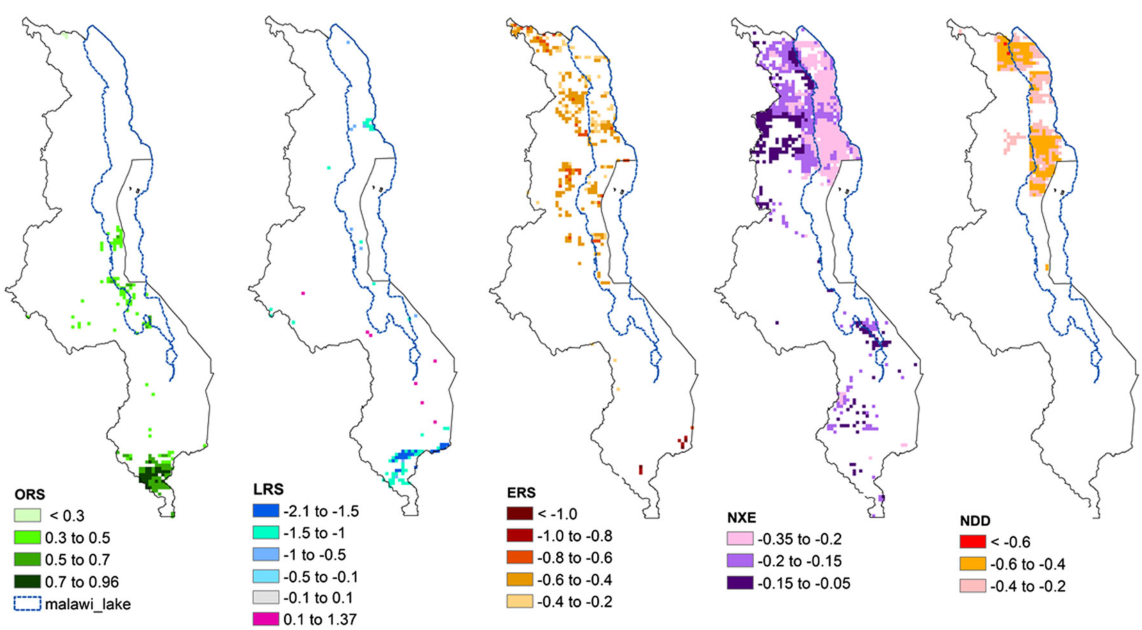

Fig. 4 Spatial distribution of magnitude of trend using Sen's slope estimator for ORS (Onset of Rainy Season), ERS (End of Rainy Season), LRS (Length of Rainy Season), NXE (Number of eXtreme Events), and NDD (Number of Dry Days) at 5% level of significance

Looking at the distributions of each index over time shows consistently high interannual variability, as well as overall variability of indices (not shown), consistent with Tadross et al. (2009). Interannual variability in ORS is positive (i.e., increasing) and shows an overall later onset trend of 5 days/decade, or ~ 20 days later since the 1980s for the green areas in Figure 4. The interannual variability of NDD is small, with a decreasing trend. Dry spells in the middle of the growing season are reported in FEWS data (FEWSNET 2017) and by farmers as being more common. The increasing trend in ERS shows that the rainy season ending has a different pattern than the ORS trend and clustered in the north; this may be due to the post-break shift in rainfall forcing (Nicholson et al. 2014) and needs to be examined further with a regional climate model to understand how these shifts are unfolding. Surprisingly, the NXE annual average shows decreasing trends only. Interannual variability of LRS is consistent throughout but a small region on the south which shows a significant decreasing trend. This contrasts with more localized reductions in LRS found by Fiwa et al. (2014).

Regional aspects

Figure 5 aggregates all five significant changes from Figure 4. Figure 6 shows the map with boxplots of two selected statistically significant regions to better explore the variability in North and South Malawi. The cutoff at the national boundary artificially makes this inappropriate for robust trend detection, but some general patterns emerged. For ERS North, the evident trend towards lowered ERS variability is spatially consistent, the overall tendency is towards an earlier ending date of 20 days earlier since the 1980s, although this is not evident in the last 4 years. There is also interdecadal variation in the interquartile range (IQR) of the boxplots showing increased extremes in the late 1980s/early 1990s and again for most of the 2000s.

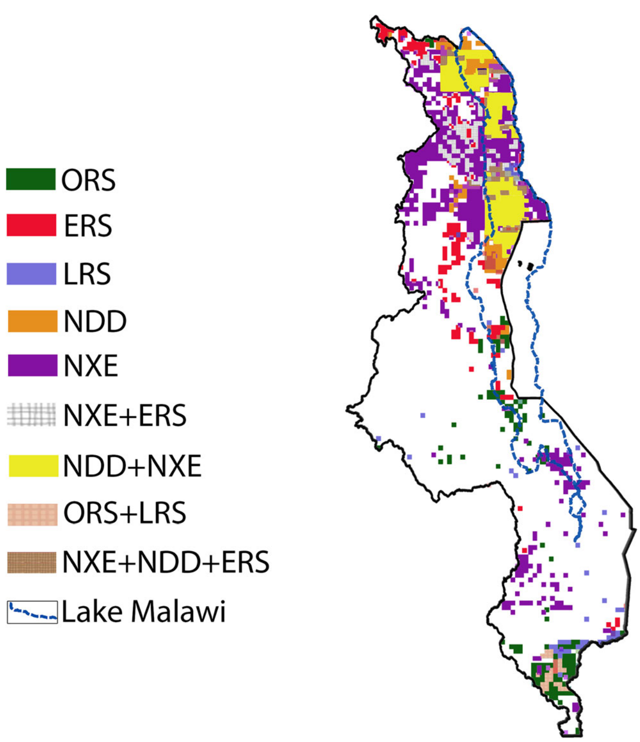

Fig. 5 Spatial aggregation of all statistically significant changes across Malawi and their overlaps; ORS (Onset of Rainy Season), ERS (End of Rainy Season), LRS (Length of Rainy Season), NXE (Number of eXtreme Events), and NDD (Number of Dry Days)

For ERS South, which just encompasses the cluster showing a positive (i.e., later cessation) trend in red in Figure 5, the behavior is less clear. The ends of major ENSO events in 1998 and 2016 are associated with a very early ERS, but overall, the positive trend in this region, since 2005, is more consistent. Variability shows no evident pattern.

The regional boxplots for NXE are more consistent for Northern and Southern Malawi, showing a reduction of both mean and IQR. This reduction is more pronounced during the last decade, with 0.2 events/year fewer. Both regions show similar distributions, suggesting that the drivers behind this decline in NXE are likely forced by global scale drivers as modified by Indian ocean SSTs (e.g., Black et al. 2003; Ummenhofer et al. 2018) and not by local-scale processes like deforestation or land cover change. However, some interesting differences occur; for example, the NXE North had peak means in 1994, 1997, 2001, and 2009. The NXE South had peaks in 1995, 1999, 2004, 2005, and 2010. These patterns are also consistent with droughts occurring more frequently than floods in East Africa (Williams and Funk 2011) and the intensification of the Indian Ocean Dipole (Abram et al. 2008).

With statistically significant changes to ORS and ERS, we expect LRS to change significantly as well. However, this is not the case. For most locations, ORS and ERS changed in the same direction, offsetting any LRS effect. Because of the high variability in both ORS and ERS, the only way a statistically significant change in LRS is likely when both ORS and ERS act together to either expand or contract LRS. Often for many locations, ORS and ERS are shifted in the same direction—later or earlier—and those LRS showed no significant change.

Although about one-third of the country shows evidence of some type of change (Fig. 5), nearly half of Malawi shows significant change but significant only at the 0.10 level (not shown). Only the central region of Malawi is free of any type of change, and many areas (especially in the north) show multiple types of change. Most of northern Malawi—where we find more significant changes in rainfall—is not in the main maize belt, and its higher elevation means that yield is constrained as much by temperature limits as by water stress.

Conclusion

Recent variability of crop yields in Malawi has been attributed to differences in weather, seasonality, and aspects of human management. However, causes of yield change are difficult to attribute, and farmers' reports speculate that rainfall change is a major factor. Here we present results to assess the nature and magnitude of these rainfall shifts. We employed the daily CHIRPS dataset at a spatial resolution of 0.05° from 1981 to 2018. We tested this gridded dataset for validity against gauge measurements and found that the correlation is high and likely an accurate dataset. We also tested the trends using three other gridded datasets including CHIRP, ARC2, and PERSIANN-CDR. We determined that PERSIANN-CDR is too coarse to capture regional variability well. CHIRPS was sufficient to estimate general trends over Malawi for our five indices, and the trends (even when using different gridded datasets) showed similar behavior with some exceptions, particularly with extreme events. The NXE differences may be due to processes involved in building gridded datasets, where on-the-ground data are sparse, or to ocean influences, or maybe some combination of the two.

The main purpose of showing the trends is to highlight the fact that much of Malawi shows no significant change for any single variable, but that there are cohesive clusters with significant changes. Some of these most persistent changes in the non-white regions of Fig. 5 showed high variability and some dramatic localized shifts:

- Delayed ORS ranging from 18 to 35 days;
- Decreased NDD about 21.6 days;
- Earlier ERS ranging from 21.6 days in the northeast and 36 days in the south;
- A broad decline in NXE of between 5 and 7 days fewer;
- Spatially isolated but strong trends in LRS ranging from 54 days less to 49 days more.

Our results show that roughly one-third of Malawi has experienced at least one type of significant change during the study period. Northern Malawi had ~ 2 fewer days/decade with extreme events and an end of season ~ 5 days/decade earlier, as well as ~ 5 fewer dry days/decade, although ARC2 and CHIRP had the opposite trend. This is important to verify and needs more ground gauge measurements. Central Malawi exhibited a variety of changes over the study period including earlier cessation in the central west, later onset in the central east, a longer rainy season in the middle, and fewer extreme events in the central east. The results are heterogeneous spatially and suggest that broad scale forcings are not driving them.

Some of these numbers are dramatic due to treating a long-term trend as linear; the actual data are very noisy with large jumps and nonlinearities. Locally clustered changes in some areas suggest that the drivers of change are likely coarse-scale. We combined all significant changes in one map and provided an aggregate zoning map of changes (Fig. 5). Accordingly, Northern and Southern Malawi have been experiencing at least one type of rainfall change, with central Malawi's trends not being significant. The most dominant changes are related to ERS and NXE. This research followed from NTX14, which found a shift to a later time in ORS and ERS, with no major change in the LRS (and not statistically significant). However,

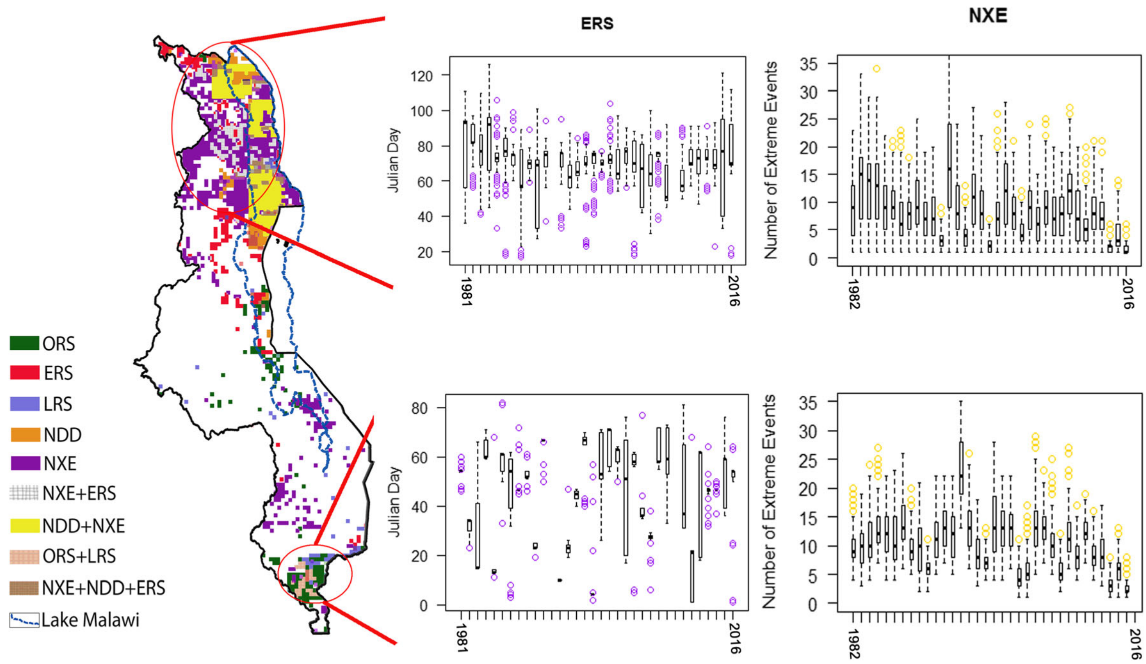

Fig. 6 Regional boxplots for NXE (Number of eXtreme Events) and ERS (End of Rainy Season) for two grouped areas; ORS (Onset of Rainy Season), ERS (End of Rainy Season), LRS (Length of Rainy Season), NXE (Number of eXtreme Events), and NDD (Number of Dry Days)

this study found similar trends with statistical significance in areas where no gauge measurements are available.

Our results do validate anecdotal farmers' perception somewhat, especially in southern Malawi, but the nature and magnitude of those changes are not consistent across Malawi. To support more practical applications, we are working on using multiple approaches for determining onset with multiple datasets in the future. We will expand this approach to more of East Africa. Our use of a single algorithm limits the validity of these results in that out onset dates may not account for erratic starts to the rainy season. As a practical application for farmers, we are mainly identifying which metrics of change are consistent across datasets and worthy of continued exploration for trend changes.

For future work, interannual and intra-seasonal variability driven by synoptic drivers versus land-use drivers needs to be explored with a regional climate model. This is in part to understand how pre- and post-"break" rainfall seasons might be responding to shifting circulations (Nicholson et al. 2014). Also, finding hotspots of robust and significant changes, then relating them to global forcings or to more localized drivers (e.g., specific changes in land cover and land use at those hotspots) would be helpful in assessing the roles and magnitudes of land-atmosphere feedbacks. In this way, understanding connections between external forcings, land use change, and rainfall together with improving drought-tolerant crop varieties will give us more tools to help farmers adapt.

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