Type of the Paper (Article)

Uncertainty in drought identification due to data choices, and the value of triangulation

Pius Borona [1,2*], Friedrich Busch[1,2], Tobias Krueger [1,2] and Philippe Rufin [2]

1 IRI THESys, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
2 Geography Department, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
* Correspondence: boronapi@hu-berlin.de

Abstract:
Droughts are complex and gradually evolving conditions of extreme water deficits which can compromise livelihoods and ecological integrity, especially in fragile arid and semi-arid regions that depend on rainfed farming, such as Kitui West in south-eastern Kenya. Against the background of low ground-station density, 10 gridded rainfall products and four gridded temperature products were used to generate an ensemble of 40 calculations of the Standardized Precipitation Evapotranspiration Index (SPEI) to assess uncertainties in the onset, duration and magnitude of past droughts. These uncertainties were driven more by variations between the rainfall products than variations between the temperature products. Remaining ambiguities in drought occurrence could be resolved by complementing the quantitative analysis with ground-based information from key informants engaged in disaster relief, effectively formulating an ensemble approach to SPEI-based drought identification to aid decision making. The reported trend towards drier conditions in Eastern Africa was confirmed for Kitui West by the majority of data products, whereas the rainfall effect on the increasingly dry conditions was more subtle than annual and seasonal declines and greater annual variation, which warrants further investigation. Nevertheless, the effects of increasing droughts are already felt on the ground and warrant decisive action.

Keywords: Droughts; Gridded data; SPEI; Triangulation; Semi-Arid; Eastern Africa

1. Introduction

Drought is a slow-onset phenomenon characterized by spatiotemporal water deficits restricting water accessibility and availability for social-ecological systems at varying temporal scales [1-5]. Characteristic persistent negative anomalies in precipitation and high temperatures leading to high evapotranspiration from soils and crops eventually have cross-sectoral effects on agriculture, food and livelihoods, particularly in East Africa where rainfed agriculture is the economic mainstay [1, 6-11]. Droughts and other environmental changes prevalent in East Africa, such as agricultural expansion and corresponding land degradation, contribute to water crises as they aggravate the competition of water demands[1]. Droughts may be categorized as (i) meteorological (resulting from rainfall deficit) or, depending on duration and additional drivers and impacts, (ii) agricultural (exceptionally low soil moisture), (iii) hydrological (exceptionally low surface and/or subsurface water levels) and (iv) socio-economic (resulting from water supply and demand failure in relation to the previous categories)[1, 4].

Droughts have severe, widespread effects on livelihoods, especially in arid and semi-arid regions, contributing *inter alia* to declining crop quality and quantity and forest productivity [12, 13], and deterioration of aquatic life [10]. East Africa, and especially Kenya, is emblematic of the recurring drought regions worldwide[10, 14-17]. The agroecosystems of semi-arid eastern Kenya are particularly vulnerable, with an inconsistent rainfall regime and the frequency and intensity of droughts increasing [3, 10, 12, 18, 19]. Kitui County in south-eastern Kenya is such a vulnerable semi-arid region with inconsistent rainfall and high temperatures, featuring dry spells in the growing season that impede the dominantly rainfed agriculture [10, 16, 20]. Water demand will likely follow the projected population increase in the area [21]; hence monitoring and understanding of drought dynamics and the development of management interventions are ever more necessary.

Precipitation and temperature are the primary meteorological variables modulating drought duration and severity. However, the impact of prevailing data uncertainties [22] in the identification of past droughts, particularly in data scarce regions like East Africa, has received little attention in the literature. Identification of past drought occurrence is essential to assess responses and mitigate against current and future events. The inherent complexity of the phenomenon due to the interrelation of hydrological and social factors in drought occurrences, impacts and responses has attracted a range of research fields across the natural and social sciences [2, 23, 24]. It seems apt, therefore, to complement the meteorological data with qualitative ground-based information from disaster response and other sources in order to verify drought identification based on gridded products. This promising approach has to date remained largely unexplored.

The Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI) are two widely used drought intensity monitoring indices. The SPI is recommended by the World Meteorological Organization (WMO) [1, 15, 25] and requires rainfall as the only parameter. The SPEI, an extension of the SPI, is a more recent statistical index where the water balance is represented by precipitation and potential evapotranspiration (PET) [26], making it arguably more reliable for the detection and monitoring of drought [26-28]. The SPEI identifies meteorological drought at a sub-annual scale but can be a proxy for hydrological, agricultural and socioeconomic drought [29].

SPI and SPEI, which are closely related indices, with the latter an improvement of the former [27, 30], have been applied to various ecosystems in East Africa. Studies have typically responded to the unevenly distributed and generally scarce station-based data over East Africa with the use of gridded data products [7, 9, 31-34]. For instance, [28] demonstrate near similarity of SPEI and SPI using MERRA-2 temperature, merged with the CHIRPS rainfall product. [35], by contrast emphasize the value of PET for drought identification, and hence the superiority of SPEI over SPI. [36] show the value of gridded data for drought assessment in the Ethiopian Upper Blue Nile Basin; in their case the CHIRPS product outperformed TARCAT, PERSIANN and TRMM. Also [37] emphasize the usefulness of CHIRPS, in the uneven topography of East Africa. They reveal the value of precipitation, and minimum and maximum temperature at monthly resolution for long-term climate variability assessment.

[9] use an array of five gridded data products to compute SPI, SPEI and soil moisture anomalies, demonstrating the uncertainty in existing products, with discrepancies particularly in mountainous areas and areas with low ground-station density. [37] emphasize the need to consider temperature variation alongside rainfall and the need for higher quality data to manage data-related uncertainties in the central Kenyan highlands. [38] provide an account of drought impacts over East African agroecosystems and the importance of temporal assessment using gridded data, further emphasizing uncertainty and spatial variability.

In the present study, we problematize the choice of rainfall and temperature products for the calculation of SPEI in the context of identifying past drought conditions in the semi-arid Kitui West area of Kitui County, south-east Kenya. We thereby complement existing studies with a demonstration of the variation of data products and the resulting SPEI calculations at the sub-national scale, which is relevant for assessing drought impacts on agriculture-based livelihoods [39]. We compare 10 gridded rainfall products with coverage of Kenya. In the absence of ground-stations within the study area, comparison is made with the two nearest in-situ stations as well. In the attempt to resolve the ambiguity in drought identification resulting from the differences in products, we show the value of complementing the SPEI analysis with key informant interviews, effectivvely demonstrating the value of triangulation. The paper is structured as follows. Section 2 introduces data and methods. Section 3 and 4 present and discuss the results in light of other studies in Kenya and East Africa. Section 5 concludes with a summary and recommendations for policy and practice.

2. Materials and Methods

2.1 Study area

Kitui County is a largely semi-arid to arid locality in south-eastern Kenya ,Figure 1, with an intermittent river regime. The county has a population of over 1.1 million persons with a density of 37 persons per square kilometer, an average household size of 4.3 and a total area of about 30,430km^2 [21]. The county is characterized by relatively high poverty levels, with indicators of food and water insecurity highlighted in the sub-national development blueprint, the Kitui County Integrated Development Plan (2018-2022) [40]. Food poverty is estimated at about 39.4% compared to Kenya's average of 32% [40]. Approximately 50% of inhabitants do not have access to water sources within a walking distance of 5km [40]. The erratic rainfall regime is considered a principal parameter linked to the viability of the mixed crop agroecosystem against the background of recurrent drought conditions [11]. As in most of East Africa, small-scale mixed crop farming is the primary livelihood in Kitui County, supporting food production among other benefits [11].

Kenya receives rainfall in two seasons, a longer one in March-May (MAM) and a shorter but more reliable season in October-December (OND) [41]. Temperatures range from 14 to 34 °C, with January-February being the warmest months followed by MAM [42]. The ecological profile of the county includes seven agroecological zones that reflect the agricultural development potential as well as varying vegetative cover. Dominant soil groups include Dystric Regosols, Lithosols and Humic Cambisols, the Ferralo category consisting of Acrisols (ferric), Luvisols and Ferralsols, and Chromic Luvisols and Ferralsols [8].

2.2 SPEI calculation

The SPEI was calculated using the *R package SPEI version 1.7* [30] for a 30-year period (1987-2016) using all combinations of 10 monthly rainfall and four monthly min/max temperature products (Table 2), yielding a total of 40 data blends. These products were chosen because they had proven reliable in the variable terrain of East Africa [28, 36, 37, 43]. A 30-year window of analysis was chosen as all products overlapped during this period. The units of all data sources were harmonized to mm/month and °C (monthly average), respectively. Monthly PET was calculated from Tmin and Tmax using the reduced data Hargreaves method in the SPEI. Following previous studies, a 12-month accumulation was used as it yielded a smoother annual drought visualization compared to 3- and 6-month accumulations, while depicting generally similar drought patterns ([28], [44]). The 12-month SPEI also represented an annual rainfall regime matching the semi-arid agro-ecology of the study area which often receives minimal rainfall. It also fits with the observed inter-annual distribution of drought instances as learned from interviews in the field. The accumulated differences between rainfall and PET were normalized using the log-logistic distribution, and fitted using the unbiased estimator of probability-weighted moments, as implemented in the SPEI package version 1.7.

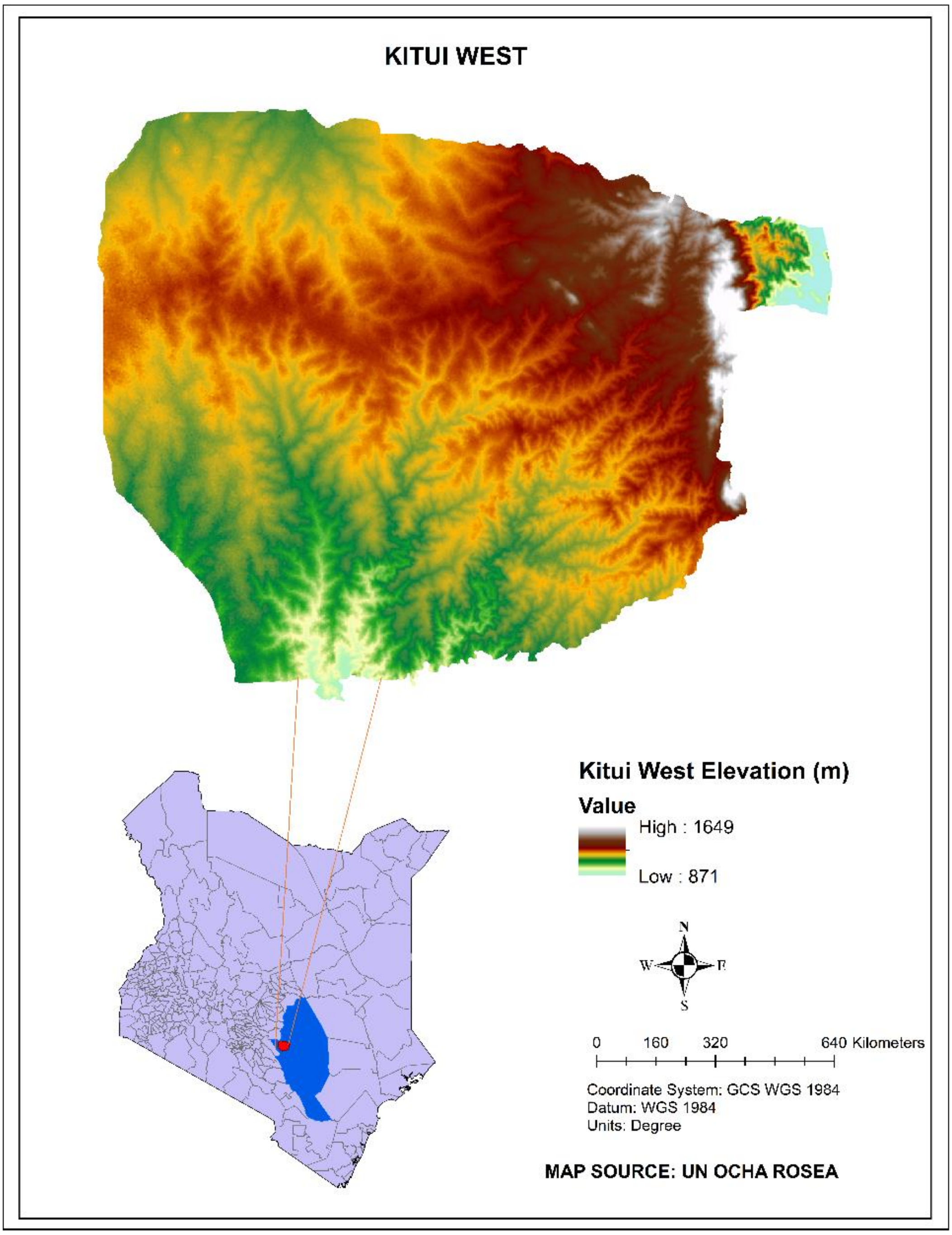

Figure 1 Map of the study area, Kitui West Sub County, in Kitui County, South-Eastern Kenya.

2.3 Meteorological data products

The nearest four synoptic and agrometeorological stations are located approximately 100-200kms away from the study area, and the nearest, Kitui Agrometeorological Station, has only a 5-year record and too many data gaps to be useful for our analysis. The same applies to adjacent volunteer stations [34]. Hence the gridded data products could only be compared to two ground-stations further away that had reliable records [34, 45]. The gridded products are summarized in Table 2.

Table 1 Characteristics of the two meteorological stations close to the study area.

Station	Long.	Lat.	Elevation (m)	Approx. distance from study area (km)	WMO Code	Station ID	Temporal coverage
Machakos	37.2	-1.5	1600	105	HKMS	9137089	1956 to date
Makindu	38.1	-2.3	1000	180	HKMU	9237000	1904 to date

The Kenya Meteorological Department (KMD) provided gridded data for Kitui West [34, 46]. This product is developed through the Enhancing National Climate Services (ENACTS) program [31, 46, 47], which works with national meteorological services across Africa to improve the quality of climate data and enhance access in essential sectors such as agriculture to counter the problem of scarce ground-based stations [31]. The KMD product combines spatially downscaled reanalysis data and bias corrected satellite-based rainfall estimates with sparse station-based observations. For Tmax and Tmin, 37 weather stations across Kenya were used and merged with data from the JRA-55 (Japanese 55-year Reanalysis) product (see Table 2 for JRA-55 background) [48]. Rainfall was generated using data from about 700 stations which were merged with satellite data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product (see Table 2) [43, 46].

The Japanese 55-year Reanalysis (JRA-55) data, produced by the Japanese Meteorological Agency, is an improvement of the predecessor, JRA-25, where problems such as cold bias in the lower atmosphere, dry bias in the Amazon and a longer time scale, since 1958, have been addressed [49]. Following [50], the product has demonstrated reliability in Central Equatorial Africa where a comparison was made with other reanalysis products including MERRA-2, ERA-Interim, 20CR, CFSR, NCEP-1 and NCEP-2. The ERA5 data is a fifth-generation reanalysis product of the European Center for Medium-Range Weather Forecasts (ECMWF) [51]. It has a longer temporal coverage and higher resolution than the predecessor, ERA-Interim, and provides more parameters at hourly resolution accompanied by uncertainty information. A study by [52] compared the performance of the product to in-situ stations, with [53] revealing the usefulness of ERA5 especially at high elevations. The Modern-Era Retrospective Analysis for Research and Applications (MERRA-2) data is a reanalysis product of the Global Modeling and Assimilation Office of the Goddard Space Flight Center developed towards the aim of an integrated earth system analysis [54]. The satisfactory performance of the product as compared to the GPCP and JRA-55 products is depicted by [55] and by [50] over Central Equatorial Africa through comparison with the new gauge-based NIC31 product alongside other reanalysis data such as JRA-55 and ERA-Interim.

The data from the Global Precipitation Climatology Centre (GPCC), operated by the German Weather Service, consists of the world's largest database of station-based precipitation data [56]. The primarily monthly data is used to develop gridded products such as the full-data, monthly version 6 which consists of the largest station number. The GPCC showed reliable performance when compared at the global level to the CRU CL 2.0 and ERA40 products at various locations. The data from the Global Precipitation Climatology Project (GPCP) of the World Data Center for Meteorology is a monthly gridded product built by merging satellite estimates and gauge analysis from the GPCC. Version 2.3 includes adjustments for improved rainfall estimates compared to version 2.2 [57]. A study over the complex terrain of the Ethiopian highlands by [7] showed the applicability of the product under those circumstances compared to the TRMM 3B43 and CMAP data. The Climatic Research Unit gridded Time Series (CRU TS) data is a gridded product based on angular distant weighting of ground-station data from national meteorological services around the world [58]. The product's performance has been compared to the GPCC.

The Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data is a merged product including five satellite-based and ground-station products [43]. It has previously proved reliable in the uneven topography of East Africa [32]. Over Kenya, the product has demonstrated remarkable performance [59] over drier regions [37] where it out-performed ARC2 and CHIRP. The latest version of the Tropical Applications of Meteorology using SATellite (TAMSAT) data (TAMSAT 3.1) merges Meteosat thermal infrared imagery and rain gauge observations covering the whole of the African continent since 1983 [60]. Alongside the TRMM 3B42 and CMORPH products, TAMSAT demonstrated high performance over the complex Ethiopian highlands in a study by [7]. Another largely satellite based product, the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record (PERSIANN-CDR), is developed from GPCP and satellite-based data [61]. The PERSIANN-CDR has proven useful in detecting disasters as [61] showed in the 2005 Katrina hurricane product verification study, comparing also GPCP, TRMM and CPS.

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Table 2 Rainfall (P) and temperature (Tmin/Tmax) products used in the computation of SPEI. Original daily data were aggregated to a common monthly resolution. Only validated and widely used products with a length of more than 30 years were used.

Data product	URL	Spatial resolution	Temporal resolution	Temporal coverage	Spatial coverage	Design application	Data sources
KMD gridded P & Tmin/ Tmax; P from ground-stations Machakos and Makindu [34]; [46]; [31]	https://meteo.go.ke/	0.0375^0 (P) / 1.25^0(Tmin/Tmax)	Monthly	before 1987-after 2016	Kenya	Drought monitoring	Gauge, satellite, reanalysis
JRA-55 P [48]; [62]	https://rda.ucar.edu/datasets/ds628.0/	1.25^0	Hourly	Since 1958	Global	Climate variability/ change monitoring	Reanalysis
ERA5 P [51]	https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=overview	1°x0.1°; native resolution 9km	Hourly	Since 1981	Global	Drought forecasting	Reanalysis
MERRA-2 P & Tmin/ Tmax [54]	https://disc.gsfc.nasa.gov/information/howto?title=How%20to%20Download%20MERRA-2%20Daily%20Mean%20Data	0.5°x0.625°	Hourly	1980-2017	Global	Climate monitoring	Reanalysis
GPCC 2018 P [56]	https://opendata.dwd.de/climate_environment/GPCC/html/	0.5^0	Daily	1891-2016	Global	Drought monitoring	Gauge, satellite
GPCP 2.03 P [57]	https://www.ncei.noaa.gov/data/global-precipitation-climatology-project-gpcp-monthly/access/	0.5^0	Daily	1901-2018	Global	Climate variability/ extremes	Gauge, reanalysis
CRU TS 4.03 P & Tmin/ Tmax [58]	https://www.chc.ucsb.edu/data/chirps	0.05^0	5 days	Since 1981	50°S-50°N	Early warning, drought monitoring	Gauge, satellite
CHIRPS 2.0 P [43]	https://www.chc.ucsb.edu/data/chirps	0.0375^0	5 days, daily	Since 1983	50°S-50°N	Risk assessment, drought insurance, early warning	Satellite
TAMSAT 3.1 P [60]	https://www.tamsat.org.uk/data/rfe/index.cgi#main-content	0.25^0	Hourly	Since 1983	60°S-60°N	Climate change/ variability studies	Satellite

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2.4 Areal averages

The meteorological data were averaged over the study area by weighted average, proportional to the contribution of each grid cell to the study area shape (see Figure. S1 and Equation. S1 of the Supplementary information). For each data product, the grids differed in their intersection with the study area (see Figure. S2 of the Supplementary Information). Correlations of the areal averages with the nearest ground-stations at Machakos and Makindu and the gridded rainfall data provided by the KMD were greater than 0.6 (see Figure. S3 of the Supplementary Information). Following [63], we used the native resolution of the products (*Table 2*) in the computation of areal averages. Nevertheless, use of standard resolution could be included in future studies, certainly when covering greater areas in East Africa where the topography is highly variable.

2.5 *Key informant interviews*

[3] recommended the triangulation of SPEI output in order to reinforce the results while also contributing to a broader understanding of the temporal evolution of droughts and ongoing responses. Following [64] we additionally view methodological triangulation (referred to as triangulation in the text and henceforth) as an optimal approach for integrating our qualitative and quantitative data to generate a confirmatory picture. Therefore, in addition to the SPEI calculations using the 40 blends of rainfall and temperature products, information on drought occurrence and severity was obtained by interviews from 14 key informants with a track record of working on droughts and related activities, e.g. food security, humanitarian and farm-based interventions, in the study region (see Table. S3 in the Supplementary Information). The interviews were conducted between August 2020 and February 2021 as video meetings and were preceded by official communication. They included discussions under the broad subjects of drought frequency, trends and history as observed in the interviewee's line of activity, nature of responses implemented with regard to water storage and on farm interventions, collaboration with the affected communities and experiences and prospects under the relatively new devolved/county governance system. The interview guide is included in the Supplementary Information, Table S3. A snowball sampling approach was used, where each key informant was asked to suggest equally active organizations in the study area for further interviews [64]. Some interviews were recorded upon consent of the interviewee; for others, notes were taken.

3. Results

3.1 Precipitation and Temperature variability

The inter-annual variability in precipitation across the study area frequently exceeds ±1mm (in 30% of the cases), less often ±2mm (5% of the cases), (Figure 2; for zoomed-in versions see Supplementary Information, Figure. S5). Mean absolute deviation is 154mm for annual precipitation, and negative anomalies are more frequent but less severe as compared to the positive anomalies. Further, at the annual level the overall products, mean= 656mm, SD=197mm and CV=32%. The data products often, but not always, agree on the direction of the anomaly (70 % of the cases), but generally disagree on the magnitude of the anomaly across all years. The precipitation products in greatest disagreement with the others were JRA-55 and MERRA-2 reanalysis. These products show positive anomalies when most of the other products agree on negative anomalies in 1993, 1995-1996 (both), 1999 (MERRA-2), 2000-2001, 2003, 2009-2010 (JRA-55), and 2013-2014, 2016 (MERRA-2), or negative anomalies in case of otherwise widespread agreement on positive anomalies in 1988 (both), 1989, 1994 (JRA-55), 2002 (MERRA-2), and 2015 (JRA-55). These two products also turned out the least correlated with other products and the measurement stations (Figure. S3; correlations between 0.5 and 0.8). The greatest inter-product agreement was found in the years 1987,1991 (negative anomalies), 1997 (positive anomaly), 2004-2005 (negative anomalies), 2006 (positive anomaly) and 2007-2008 (negative anomalies). The greatest disagreement was found in the years 1989, 1992-1993, 1995, 1998, 2001, and the more recent years of 2010, 2012-2013 and 2015-2016.

There is less variation in the Tmin/Tmax unlike precipitation (mean= 29.97 ^{o}C, SD=0.86 ^{o}C, CV=1.74%; mean=17.59 ^{o}C, SD=0.302^{o}C, CV=1.67% for Tmax and Tmin, respectively). The Tmin/Tmax products are more similar in inter-annual pattern than magnitude (Figure 3). KMD and MERRA-2 largely agree both in terms of max temperature pattern and magnitude, whereas CRU and JRA-55 show a similar pattern but lower values (see Table. S1, Supplementary Information for means and coefficients of variation). When it comes to Tmin, the products are largely in agreement in terms of pattern, but not in magnitude with mean Tmin decreasing in the order KMD, JRA-55, MERRA-2, CRU (see Figure 3 and Table. S1). The agreement in pattern can also be seen in the correlation analysis (Figure. S4; all coefficients greater than 0.8).

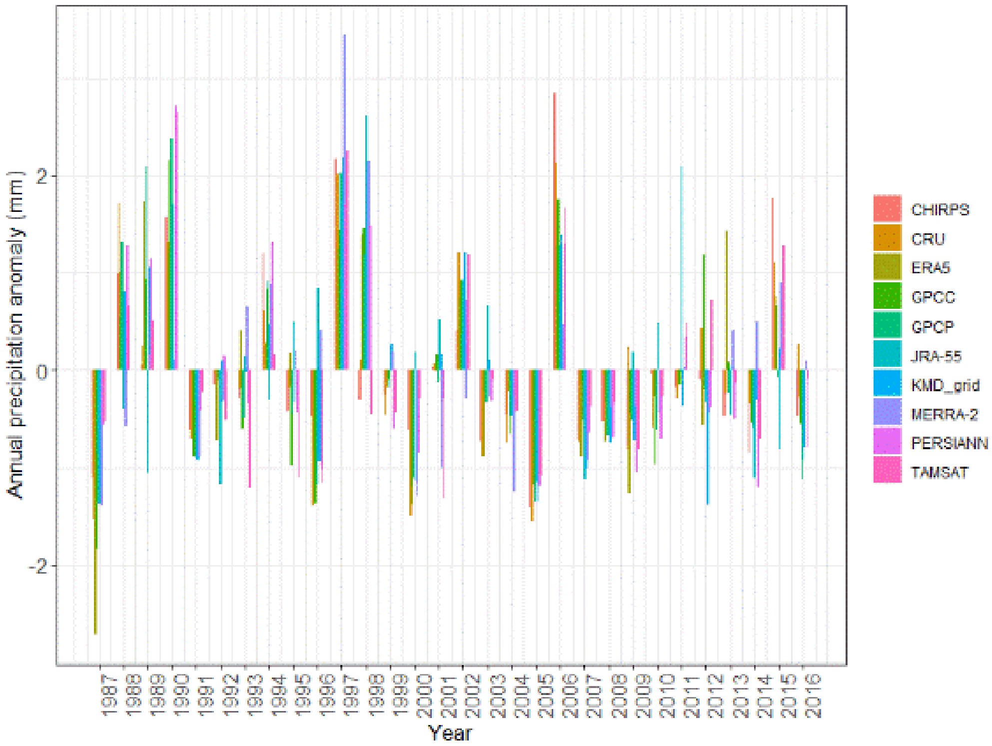

Figure 2 Annual precipitation anomalies as conveyed by the different data products.

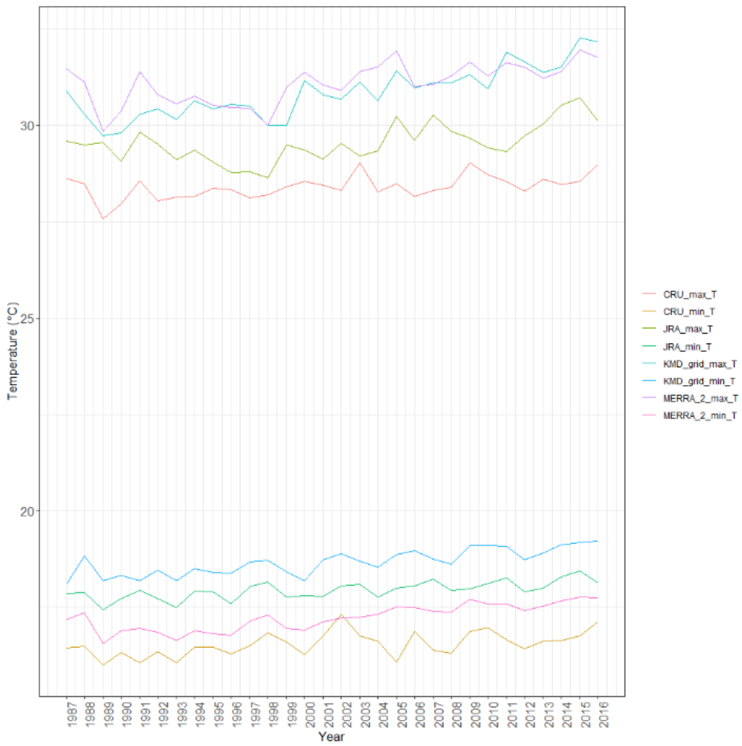

Figure 3 Annual maximum (Tmax) and minimum (Tmin) temperature time series as conveyed by the different data products.

3.2 *Precipitation and Temperature trends and SPEI-based drought identification*

All products agree (at the 0.01 significance level) on an upward trend of Tmin of about 0.02-0.03°C per year and of max temperature of about 0.02-0.06°C per year (Figure. S6, Supplementary Information). The rainfall products annual sums show no trend or a declining trend, but none of these are significant at the 0.01 level (Figure. S7, Supplementary Information). The standard deviations of rainfall likewise show no significant trends (Figure. S8). The same applies for seasonal trends (Figure. S9). Despite the differences in the precipitation and temperature products, once propagated to the SPEI the differences smooth out, yet differences in onset, duration and magnitude of drought remain (Figure. S10 and Figure. S11 to S14, Supplementary Information).

Out of the 40 blends, 18 agree on a statistically significant (at 0.01 level) trend in SPEI of 0.0001 to -0.0098 units per month, suggesting increasing instances of drought occurrence (Figure. S11 to S14, Supplementary Information). Those trends are consistent across the temperature products with CHIRPS, GPCP, KMD_grid and PERSIANN rainfall, sometimes with ERA-5 and JRA-55 and in one instance with CRU rainfall, (Figure. S11 to S14). Plotting the SPEI mean and standard deviation across the product blends further consolidates the picture (Figure 4). Unambiguous drought years, as far as the data products are concerned, are 1994, 1996-1997, 1999-2000, 2005-2006, 2009 and 2011. More ambiguous are 1988, 1991-1993, 2001-2004, 2008, 2010, 2012-2016. Drier conditions in recent years, as suggested by the trend analysis, can be seen in 2005-2006 and 2008-2012, compared to more positive anomalies in the 1990s.

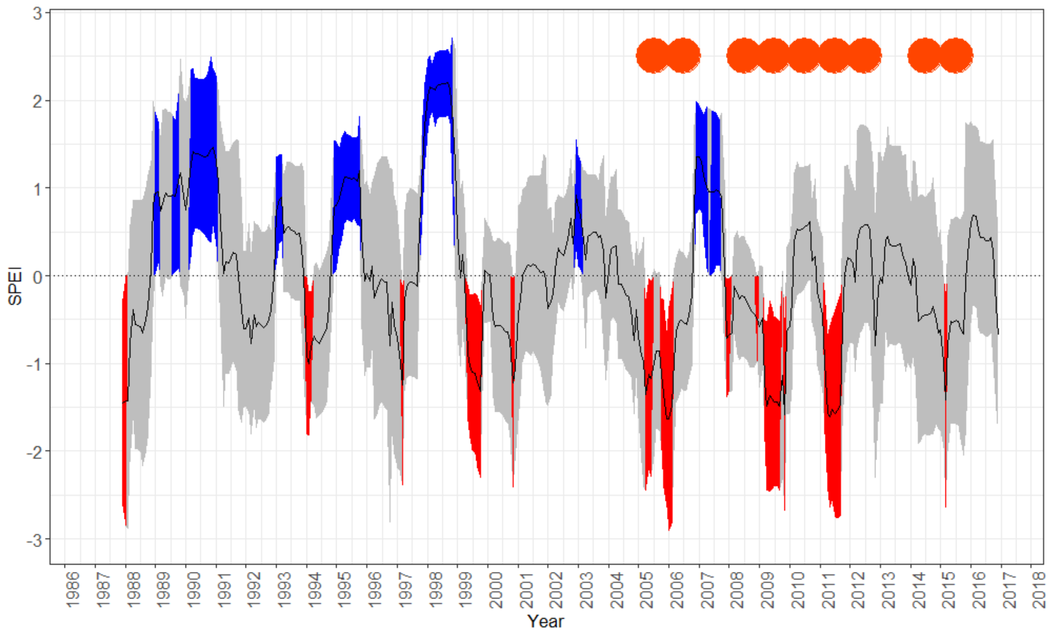

Figure 4 Inter-product SPEI mean (line) ± 2 standard deviations (shading), compared with key informant information from 2005 to 2016 (dots). Periods where mean SPEI ± 2 standard deviations were below zero are coloured red, those above zero blue.

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The information from the key informant interviews agreed with all unambiguous droughts in the timespan (2005-2006, 2009, 2011) and the one year which was unambiguously wet (2007). The interviews also pointed to droughts in 2008, 2010, 2012 and 2014-2015 where the SPEI information based on the different data products was ambiguous. In the other ambiguous years 2013 and 2016, the key informant interviews pointed to no drought. Hence it would seem that key informants engaged in drought relief on the ground in the region can resolve the ambiguity resulting from the disagreement between meteorological data products.

4. Discussion

4.1 Uncertainty in rainfall and temperature estimates and propagation to SPEI

Reliable assessment of the onset, magnitude and duration of drought is vital in agro-pastoral ecosystems, not only to understand impacts on livelihoods but also to signal and assess the reliability of responses [2, 65]. In the absence of reliable meteorological data as a result of sparse in-situ station density over Kenya [16, 34, 37] and other African countries, rainfall and temperature data from gridded products can overcome data scarcity for large-scale drought assessment [7, 59, 66] . These products, however, are subject to uncertainty, including gauge-level measurement errors in the underlying station data, the number and representativeness of the stations used, interpolation steps, structural, parameter and general input data uncertainties of the meteorological models used [22].

The abundance of gridded data products available thus creates both a challenge and an opportunity for users. Choosing a single product can lead to biased drought estimations [67], hence the use of multiple products is preferable [68]. Such an ensemble approach will add uncertainty information to the gridded products that can improve decision making in response and management operations [67]. Uncertainty in drought magnitude should in no way instill a sense of complacency as increasing extreme events such as droughts over East Africa have already resulted in deterioration of livelihoods and ecosystem integrity [69-71].

In the current study uncertainty manifests itself in differences between the data values of gridded products, for rainfall and temperature, with annual minimum and maximum temperature varying less between data than rainfall, as depicted in the results section.The temporal pattern of the Tmax and Tmin input was also more similar across products than that of rainfall. The variation of SPEI across data blends therefore predominantly reflects the variation of the rainfall data. Plotting the SPEI ensemble mean ±2 standard deviations identified periods of unambiguous dry and wet years, while ambiguous periods could be resolved by information from key informants engaged in drought relief on the ground. It should be noted that the uniform weighting of SPEI ensemble members neglects the similarity between some of the data blends, as they use similar data and assumptions, which are, however, hard to disentangle and quantify in an alternative weighting scheme. Drought occurrence was thereby much less ambiguous than drought severity. Further research is required to mitigate and report uncertainties in drought severity estimations as it is an important variable for planning appropriate responses.

4.2 Annual and seasonal trends

By comparing 10 precipitation products, we found no evidence of a statistically significant trend (although there could be a trend), neither in annual rainfall nor seasonal rainfall totals, nor annual standard deviations. This finding is in contrast with the declining rainfall trend over East Africa reported by [71], [72], [38], [41] and [11]. It is also in contrast with the key informant information that the March-April-May rain season, being the longer of the two seasons and essential in the farming calendar, has demonstrated unreliability in recent years. Since rain-fed agriculture is the primary source of livelihoods in the study area and the primary contributor to the economy [38, 40], a decrease of rainfall in the long season and a general shortening of the season is a major concern [73]. However, the reported unreliability of the March-April-May season in recent years could also be reflective of generally drier soil conditions in response to the positive temperature trend which we did find across all data products, or changes in sub-seasonal rainfall timing that are not visible as a trend in annual standard deviations. Both would propagate to lower SPEI values, which in our case and for most products agree with an increase in drought instances in recent years.

The absence of evidence of a significant trend in the shorter October-November-December rain season in our case (see Figure. S9, Supplementary Information) differs from recent studies over Kenya [41]. The key informants and the Kenyan Government [74], however, support our finding by mentioning that the shorter OND season has shown more reliability in supporting farming compared to the longer MAM season. This is manifested by greater seasonal rainfall averages in the OND season in most products (Table. S2, Supplementary information). The OND season, however, shows greater variation than the MAM season (Table. S2) as also reported by [75]. The MAM, especially due to its lower variability, thus remains important for agroecosystem productivity in the region, with a likely atmospheric teleconnection with the OND as shown by [71]. The MAM season plays a primary role in the farming calendar of the study area, accounting for about 30% of crop productivity, and supporting cultivation of staple pulses such as pigeon peas and green grams [74].

With regard to temperature, all data products compared in this study agreed on positive trends in min/max temperatures. While the products were in greater agreement about the magnitude of the Tmin trend, the Tmax trend magnitude varied more between products. This agrees with findings over Kenya by [76] who found increasing trends of min/max temperatures and [39] who similarly reports a marked warming in the Horn of Africa. [10] found warm days to be increasing and cold nights to be decreasing, as well as summer days to be increasing over Kenya, confirming the picture of rising temperatures.

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4.3 Anomalies, drought identification and the value of triangulation

The 10 different precipitation products compared in this study generally agreed on years with negative rainfall anomalies. However, the products disagreed considerably on the magnitudes of those anomalies. The anomalies demonstrate the prevailing inter-annual variability in the study area [75]. The anomalies propagated to droughts of varying magnitude, confirmed by unanimously negative SPEI values or key informants in (27%) of the 30 years. However, in 1988, 1991-1993 and 2001-2004 there was disagreement between the products and the key informant information did not reach that far back.

The 2010-2011 period is widely reported as the worst drought in a 60-year span in the Horn of Africa [71, 77]; [19]; [11], which is confirmed by the key informants for the study area but unanimously confirmed by the SPEI products only for 2011. While in most years the multi-product approach allows us to robustly identify drought and get a handle on the uncertainty in drought magnitude, from 2008 onwards, the greater disagreement between the data products, both in terms of SPEI direction and magnitude, highlights the potential of information from actors engaged in drought relief in the region. Key informants worked in disaster risk management, food security, water storage/harvesting and climate change resilience building, i.e. sectors that are sensitive to drought conditions. These experts' inputs are therefore viewed as important in the continued assessment and response to droughts.

Particularly, these inputs are valuable in drought assessments for relatively constrained spatial extents, as informant data on droughts can be assumed to cover the entire study area. For large-area drought estimations covering larger regions or featuring more localized droughts, spatially explicit information on the location and extent of informant activities must be collected during interviews and integrated into the verification of the drought occurrence estimation.

According to the EM-DAT global disasters database [78], the year 2010 experienced large scale drought conditions in the coastal, northern-most and north-eastern locations. Our analysis suggest that the 2010-2011 drought conditions had existed already since 2008 and continued until 2012, even though the year 2010 showed wetter conditions in some of the products as also confirmed by [70]. The effects of the severe 2011 drought might have carried over to 2012, with SPEI showing no sign of relief, although the actual magnitude of SPEI is ambiguous in that year. The effects of this prolonged drought period were devastating among the households largely dependent on rainfed agriculture. Essential sectors such as energy, which is largely hydro-based, were negatively impacted across East Africa [2, 6]. In Kenya, a total of 3.75 million persons, primarily in the North and parts of the South-East, were affected by the resulting food shortage according to the global record of mass disasters occurrence [78]. The drought period 2005-2006, confirmed by most products, was followed by wetter conditions in 2007, which exacerbated impacts. As [18], [77] and [38] discuss, livelihoods and natural ecosystems across East Africa were severely impacted by the drought and, as [70] reiterates, subsequent flash floods. The drought conditions seem to have commenced in 2004 and peaked in 2006, a classic demonstration of the evolving nature of the hazard [4, 23].

A case of disagreement between the SPEI blends are the years 2014-2015, which were confirmed as drought years by actors engaged in drought relief in the area and the EM-DAT database. EM-DAT mentions the year 2014 with only few areas in northern and north-eastern Kenya affected. In this light, south-eastern Kenya, including Kitui West, might have seen milder drought conditions. The National Drought Management Authority of the Kenyan government (NDMA) reports that in 2013-2014, during the OND, the greater Kitui region experienced moderate drought conditions and instances of decline in crop production and crop failure [79, 80]. Triangulation of the SPEI calculations with qualitative information on the ground showed its greatest value here. The qualitative input effectively resolved the ambiguity between the data products. However, the qualitative data, too, have the potential for errors, including false recollections, difficulties in estimating the length of a drought and distinguishing trends and extremes, influences of recent events and media attention on past occurrences, and willfully biased responses with the aim to attract funding by exaggerating the severity of the drought situation [81]. On their own, the qualitative data lack information on drought magnitude and timing, which is something that the SPEI analysis can provide, albeit with uncertainty.

5. Conclusions

Using an ensemble of gridded meteorological data products in the calculation of drought indices, such as the SPEI in this study, facilitated greater understanding of the uncertainties in onset, duration and magnitude of past droughts. These uncertainties were driven more by the variation between rainfall products than temperature products in our case. Understanding past droughts is important to study their social-ecological impacts and assess the adequacy of responses. Our study thus holds an important lesson for studies of past droughts: using any one of the available data products would risk severely misrepresenting drought characteristics. It is equally important to bear in mind that, in the absence of a dense ground-station network, there is no benchmark dataset against which the individual data products can be assessed. Searching for a “best” product is thus not viable, and the value of these products can only be realized in an ensemble.

An ensemble approach to SPEI could not, however, identify all droughts unanimously in our case, using an ensemble of 10 rainfall products times four temperature products over the Kitui West area in south-east Kenya. This ambiguity could only be resolved with the information from key informants engaged in disaster relief on the ground. Our study thus demonstrates the value of triangulating quantitative drought analysis with qualitative data. The qualitative data alone, in turn, would miss information on drought onset, duration and magnitude; this is what the ensemble approach to SPEI provides, albeit with uncertainty. It is thus the juxtaposition of both types of data that is most fruitful.

Engaging organizations involved in disaster relief locally in drought identification will also strengthen their role in the region. Since drought is a gradually evolving phenomenon with long-lasting socio-economic impacts, there is need to develop and/or intensify integrated interventions and capacity building where affected communities are actively engaged at sub-national levels. The evolving and complex dry conditions accompanied by uncertainty are a challenge for the relatively recently devolved Kitui County administration, which has the mandate to coordinate multistakeholder risk management strategies at county-level. Such management strategies and collaborative networks should be flexible to detect, track and respond effectively to various unique drought episodes. Effective responses include enhancement of government, private sector and community based disaster relief systems, targeting, for example, crop diversification with cultivation of drought resistant varieties as championed by the Kenya Red Cross [82]. An ensemble approach to SPEI will provide the necessary quantitative basis for these policies, while the experience of community, regional and national organisations will help resolve data ambiguities as well as strengthen the implementation of national policies.

Appreciating uncertainties in drought characteristics should in no way distract from decisive action for mitigating the impacts of droughts, improve disaster relief and strengthen adaptive capacity, because extreme events such as droughts have been increasing over East Africa and have already resulted in deterioration of livelihoods and ecosystem integrity. While there is likely spatial variation over the region, we confirmed a statistically significant trend towards increasingly drier conditions also for Kitui West with just over half of the SPEI ensemble members. This trend was partly driven by a significant increase of minimum and maximum temperature over time in all data products, while negative annual and seasonal rainfall trends in some of the products could not be proven statistically significant. Beyond the temperature, and therefore evapotranspiration, effect, it will be worth investigating next how the timing and sub-annual variation of rainfall propagates into negative SPEI values, i.e. drier conditions. Such an analysis should go beyond trends in annual standard deviations of rainfall, which in our case did not turn out significant either.

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Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Figure S1: Illustration of the areal weighting approach, Figure S2: Various grid resolutions of the data products used and their contribution to the areal average, Figure S3-S4: Correlation matrices between the weighted gridded rainfall products and KMD Gridded data and the weighted gridded Min/Max temperature and the KMD Gridded data, Figure S5: Annual rainfall anomalies conveyed by the Gridded products Zoomed in at the respective decades, Figure S6-S7: Annual Max/Min and rainfall trends of the 10 Gridded products, Figure S8: Annual rainfall standard deviation trend of the 10 Gridded products, Figure S9: Seasonal (March-April-May, October-November-December) precipitation trends for the 10 Gridded products, Figure S10: Cumulative negative SPEI (dry conditions) for all 40 product blends., Figure S11-14: SPEI outputs using CRU,MERRA-2, JRA-55 and KMD_grid Tmax/Tmin with the 10 rainfall products, with linear trend superimposed., Table S1: KMD-Grid, CRU , MERRA-2 and JRA-55 Tmax/Tmin Statistics, Table S2: Seasonal (MAM and OND) and Annual precipitation statistics, Table S3: Key informants involved in the study and breakdown of guiding questions., Equation S1: Steps used in weighting of respective Gridded products.

Author Contributions: Conceptualization, methodology, investigation and project administration P.B. and T.K.; Software, F.B.; Validation, P.B., F.B. and T.K.; Formal analysis, F.B.; Resources, P.B and T.K.; Data curation, P.B and F.B.; Writing—original draft preparation, P.B and T.K.; Writing—review and editing, P.B , T.K and P.R.; Visualization, F.B, T.K., P.B.; Supervision, T.K and P.R..; Funding acquisition, T.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research including the APC, was funded by Geo.X Research Network for Geosciences in Berlin and Potsdam, grant number SO_087_GeoX.

Data Availability Statement: The data used in the article can be accessed as detailed under, Table 2, the corresponding author can readily provide further clarification on a need basis.

Acknowledgments: We are grateful to the Kenya Meteorological Department for providing the requested gridded and ground station data. Further, we are equally thankful to the various gridded data providers as accessed in the respective interfaces and the input of Key informants.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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