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Scales for rating heavy rainfall events in the West African Sahel

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ABSTRACT

In the field of climate services, characterization of rainfall extremes is useful to identify and quantify rain rates that can trigger floods, on-farm water stagnation, excess run-off causing arable soil depletion and other natural hazards. Delving through multiple sources of observational uncertainties, we define extreme rain events (EREs) using the 99th percentile thresholds of daily accumulated rainfall, extracted from historical data records (1960–2016) of manual and tipping bucket gauges. The results of the analysis show that the average amplitude of these threshold values has been increasing in the recent years. Meanwhile, the three categories of heavy rains exhibit an intra-seasonal timing that follows different phases of the West African monsoon. Category 1 & 2 occur mostly in the northern Sahel, between weeks 27 and 35 of the year with an accumulated daily amount varying in the 37–65 mm range and less than or equal to 85 mm/day respectively. In category 3, rain rates are greater than 85 mm/day, observed between 28th and 38th week-of-the-year predominantly in the southern and western of the Sahelsub-region. For each category of ERE, high risk areas are mapped using the relative probability of occurrence at local scale. This classification can be exploited for forecasts verification, climate model evaluations and operational early warning services against high impact rainfall events.

1. Introduction

As the climate of the West African region is changing, a new pattern of rainfall variability has emerged since the 1990s (Lebel and Ali, 2009; Nicholson, 2005), characterized by a mixture of intense rainfall (Giannini et al., 2013; Panthou et al., 2014; Maidment et al., 2015; Sanogo et al., 2015), long dry spells (Salack et al., 2014; Sarr et al., 2015) and sequences of floods events (Panthou et al., 2014; Zahiri et al., 2016). Since 1990 many West African countries reported frequently flood events. 1.7 million people were affected by floods in Benin, Burkina Faso, Chad, Ghana, Niger, Nigeria, and Togo in 2010 (Sarr, 2011). In 2009, Benin, Burkina Faso, Niger and Senegal all experienced major floods. In 2012 more than 80% of Nigeria was affected by heavy rains which submerged much of Delta and Bayelsa states in the south-east, affecting some 350 communities and making 120,000 people homeless. In 2012, UN agencies estimated that over 16 million people in Mali, Sudan, Niger, Burkina Faso, Senegal, The Gambia, and Chad were affected by drought (UCDP, 2017). This mixed dry and wet (i.e. hybrid) rainfall distribution is attributable to global warming through internal variability of dynamic factors of the regional atmosphere (Janicot et al., 2015; Salack et al., 2016). Its impacts on water-food-energy nexus include yield/biomass loss, reduced growth, and development of crops but also farm flooding, water logging of low land crops and arable soil erosion (through excess runoff), power and energy losses. Subsistence farming, water management, and socio-economic sectors need highly precise information on rainfall extremes, but also need practical advisory on how this information can be translated into operational actions.

While extreme events are generally multifaceted phenomena (Zwiers et al., 2013; Sillmann et al., 2013), the spatiotemporal variation of heavy rainfall events is the main driver of floods. However, from event scales of minutes to hours at local and synoptic scales, quantifying extreme rainfall rates remains a challenge (Zahiri et al., 2016) as ground observation networks of this region have deteriorated, in most cases their technology is outdated (Jones et al., 2015), and modern equipment and forecasting tools are full of uncertainties (Habib et al., 2001; Sillmann et al., 2013). The Expert Team on Climate Change Detection and Indices (ETCCDI, https://www.wcrp-climate.org/data-etccdi) and the Expert Team on Climate Risk and Sector-specific Indices (ET-SCI, http://www.wmo.int/pages/prog/wcp/ccl/opace/opace4/ET-

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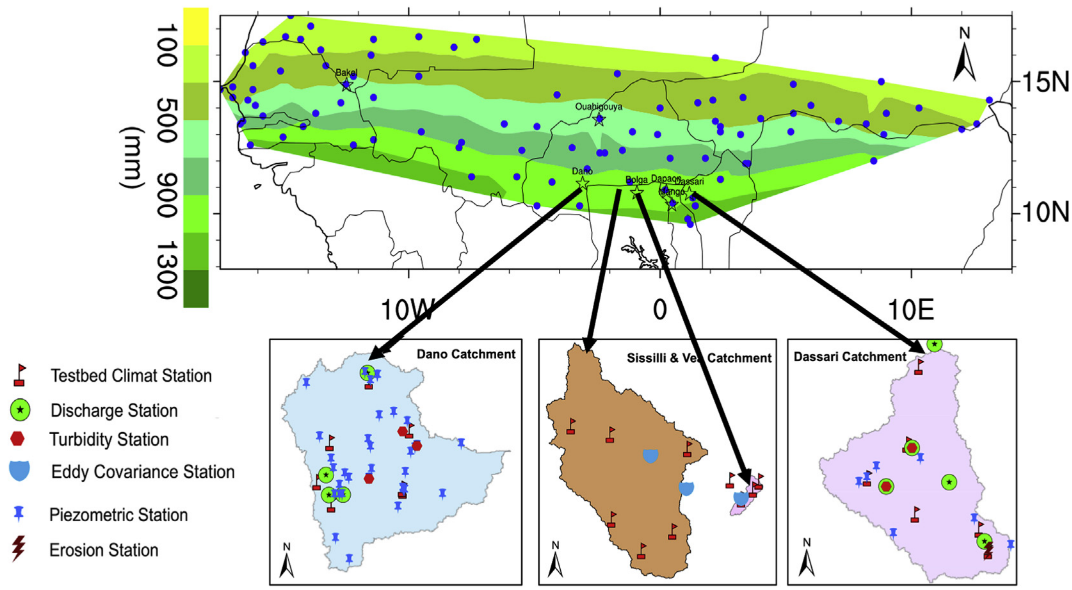

Fig. 1. Rainfall climatology (1986–2015) of the Sahelregion of West African and the WASCAL testbed catchments (Dano, Sissili/Vea & Dassari catchments) and pilot sites (*) where cutting-edge hydro-climate sensors are running.

SCI-4-1.php) have attempted to facilitate the analysis of rainfall types by defining a set of indices that provide some definitions of extremes. But, the relative dependency of the indices to baseline periods of analysis weakens their definitions of heavy rain events. Hence, identifying and quantifying extreme rain events (ERE) has been the focus of many recent studies (e.g. Ta et al., 2016).

In this study, we rate and classify intense rainfall events in support of operational monitoring, forecasting, and early warning services in the Sahel. The assessment is based on a novel hydro-climate framework of observation systems developed by the West African Science Service Center on Climate Change and Adapted Land Use (WASCAL, www.wascal.org) and partners in the region which is integrated into the regional hydro-climate observation networks. The network of testbed sites, collecting cutting-edge data since 2012, is used to rate uncertainties across scales and across rain gauge types based on 99th percentile thresholds of daily accumulated rainfall. Historical data sets from the transboundary observation network, shared with the national weather services of member countries, are used to upscale the catchment scale identification scheme, in order to classify ERE into categories embedded with warning flag colors. Section 2 of this document provides a detailed description of the observation networks and data used and sources of uncertainties found in depicting local scale extreme rainfall. The criteria of identification of intense rainfall events are exposed in section 3. The results of this study are described in section 4 & 5. The discussion and conclusions are given in section 6.

2. WASCAL observational networks

A solution to improving the quality of climate information in West Africa is to provide the region with a reliable data provision service through the modernization of the hydroclimate observation sensors, data collection systems, and related infrastructure. Recently published studies confirm that, in West Africa, this near-surface network of manual stations has substantially deteriorated over the past three decades (Lorenz and Kunstmann, 2012). The spatially loose and unevenly distributed stations which are still functional exhibit obsolete, damaged and non-calibrated instruments, the data transmission, typesetting and archiving are manual, paper-based and the operational staff is retiring often not replaced (Jones et al., 2015). To improve the availability of high quality hydro-meteorological measurements and increase our understanding of land-atmosphere processes and their interactions in the context of climate variability and change, advanced and modern near-surface observational systems are needed in West Africa. Since 2010, WASCAL has designed a set of observatories in close collaboration with its member countries, Germany and other partners (Bliefernicht et al., 2018). The main objective of observatories is to keep long-term and high quality records of micro-scale biophysical processes information by establishing sustainable near-surface observation networks (WASCAL ONs) with the national institutions of member countries (Benin, Burkina Faso, Côte d'Ivoire, The Gambia, Ghana, Mali, Niger, Nigeria, Senegal and Togo) and other partners. WASCAL ONs was formally defined as a multi-stakeholder framework of observation systems (integrated into national observation grids) which co-designs, shares data through country-specific policy and co-implements observation activities such as i) rehabilitation of existing instruments, sites, and observatories; ii) increasing the number of observation sites/stations by adding new locations; iii) rescue paper/microfiche archives of historical data by digitization; iv) improving data processing techniques; and v) train technical country institutions' staff involved in observations & related services. WASCAL ONs has two components. The first component is the regional or large scale observations network which is a transboundary sets of near-surface observation sensors, shared with national institutions of member countries. The data collection and sharing processes are governed by country-specific "third party" data sharing policy signed by WASCAL and the contracting institution of each country. The establishment of the transboundary observation networks has made progress between 2014 and 2016 with the acquisition and installation of fifty automatic weather stations across West Africa.

The second component of WASCAL ONs is the mesoscale testbeds also called "*core research watersheds*" of WASCAL include Dano catchment (600 km^2) in South-West Burkina Faso, the Vea & Sissili catchments (300 km^2 and 12,633 km^2 respectively) in Northeast Ghana and Dassari catchment (200 km^2) in Northwest Benin (Fig. 1) and projects' pilot sites. The objective of the testbed *in-situ* measurements is to install multiple cutting-edge sensors to keep long-term monitoring records of hydro-climate and land use processes from local-to-catchment scales (Bliefernicht et al., 2018). The collected panel data is a fundamental asset to improve our understanding of uncertainties in near-surface observations and useful for the calibration of biophysical models. The current hydro-climate observations equipment in WASCAL research catchments is summarized in Table 1.

Table 1
The mesoscale testbed equipment manned by WASCAL in Dano, Dassari, and Vea/Sissili catchments.

Type of Station	Dano	Dassari	Vea/ Sissili	Total	Records start
Automatic Weather station	8	7	12	27*	2012–2013
Eddy-covariance station	0	0	3	3	2012
Soil water station	3	2	3	8	2012
River gauging station	10	5	8	27	2012
Turbidity station	3	3	1	8	2012
Soil erosion and runoff plots	3	1	2	3	2012
Sediment Sampler	3	1	0	4	2012

* Datasets used in the current analysis.

The testbed weather observing stations consist of twenty-six automatic sets of meteorological sensors with a global positioning System (GPS), a GSM/GPRS communication link, a solar panel and battery, a lightning/grounding rod and a data logger. Each set has a pyranometer for measuring the incoming shortwave radiation and a two-dimensional sonic anemometer for measuring horizontal wind speed and wind direction. In addition, a silicon bandgap temperature sensor and a capacity humidity sensor protected by a radiation shield are used to determine air temperature and relative humidity. There are soil moisture and temperature probes at different depths. The air pressure is measured using a capacity pressure sensor. The total precipitation amount is recorded by tipping bucket rain gauges. In Dano (South-West Burkina Faso) and Dassari (Northern-East Benin), two rain gauges are installed in parallel, located at only 2 m from each other and connected to a central unit of data logger (Photo 1). The two tipping bucket gauges are available with a 0.2 mm sampling resolution. The rain gauges provide simultaneous records of rainfall events, enabling easy inter-comparison of records, critical in quantifying the rates of uncertainty in observations. The weather observation systems are regularly maintained every two weeks for all rain gauges and twice a month for other sensors. In the case of tipping bucket gauges, routine maintenance consists of checking the filter cleaning, removing any debris, leaves or anything else that may obstruct normal water flow. The rain gauge is usually opened to check that in the tilting bucket there are not soil residues, sand or other blocking debris. The collected data consists of nine meteorological variables: incoming shortwave radiation (Wm^{-2}), air temperature (°C), horizontal wind direction (°), horizontal wind speed (ms^{-1}), relative humidity (%), air pressure (hPa), precipitation amount (mm), soil moisture (8 depths) and soil temperature (5 cm, 10 cm, 50 cm depths) sampled every 5 min interval. At the end of every record year, the retrieved data is subjected to a quality control post-processing. All datasets and derived products are open access at geoportal https://wascal-dataportal.org/wascal_searchportal2/. The data is provided for a period ranging from the start of the measurements in early April 2012 (2013 for others) to date and the management and ownership are to WASCAL. The data collected from WASCAL ONs are used for the development of reliable modeling approaches, for determining the impact of local land cover changes, environmental energy exchanges (Quansah et al., 2015, 2017; Bliefernicht et al., 2018), for rating observational uncertainties and supporting operational monitoring and early warning services against climate extreme events.

3. Identification scheme for intense rain events

An extreme rainfall event (ERE) is defined as the exceedance of a threshold that corresponds to the 99th percentile of daily rainfall amounts observed in a season. To compute the 99th percentile for each station, we create a vector of daily rainfall values RR (RR ≥ 1 mm) of each year, sorted in ascending order. Then, we multiply 99% by the total number of those values of this vector to generate a rank index (if the index obtained is not a whole number, it is rounded to the nearest whole number). The rank index is used to extract the corresponding value from the ordered vector. This value is considered the 99th percentile threshold value. The latter is used to extract all rainfall amounts greater or equal to it in each season's record. Each ERE case(s) of a season is (are) identified with respect to the date(s)-of-occurrence (DTO) and the daily amount(s) (INT). At each rain gauge location, any daily accumulated rainfall amount is considered as extreme rainfall if it

Photo 1. Automatic weather station set-up in Dano catchment with two parallel tipping bucket gauges to depict rainfall uncertainties.

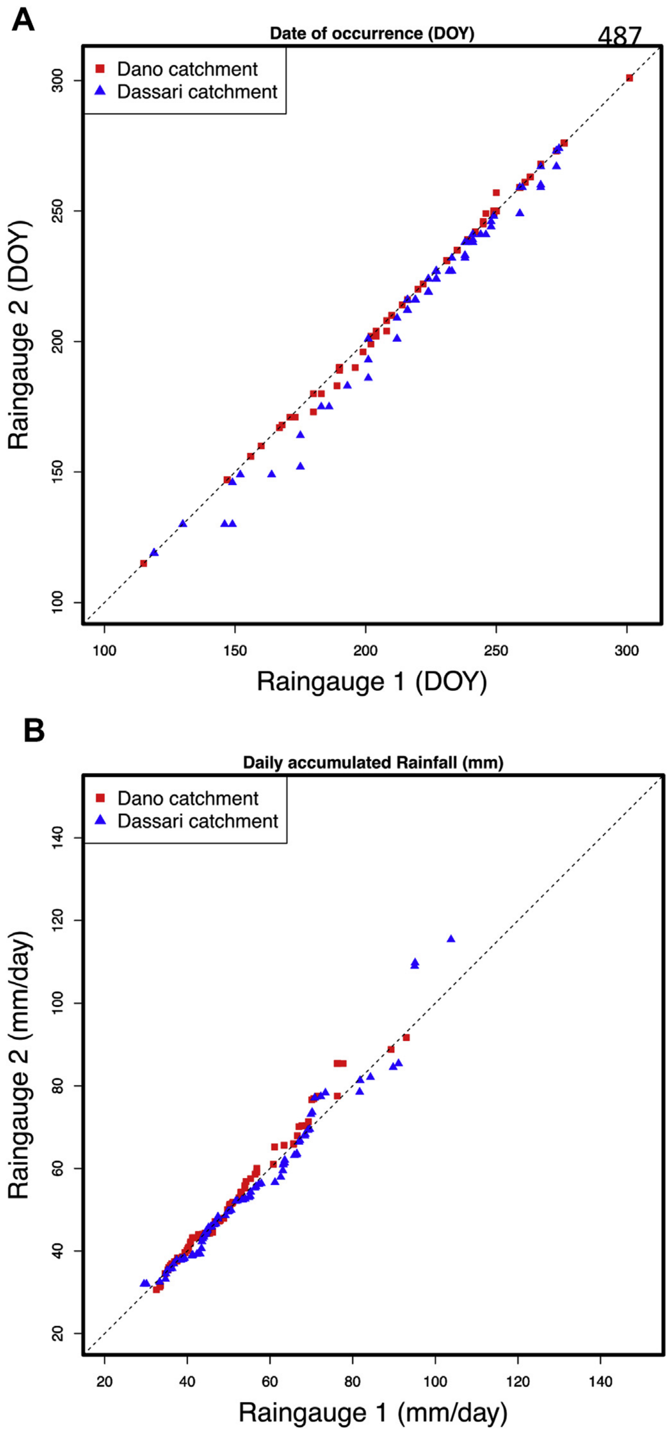

Fig. 2. Dates of occurrence (**a**) and accumulated daily rain rates (**b**) depicted by two parallel tipping bucket gauges in Dano and Dassari catchments.

belongs to the class of ERE which is greater than or equal to the 99th percentile threshold values. The analysis of the near-ground records of the ERE depicted at Dano and Dassari catchments show that the two parallel rain gauges report the same DTOs but fail to agree to the accumulated daily rain rates associated with ERE when INT is above 50–60 mm/day (Fig. 2). This discrepancy may be linked to the basic functionality of tipping buckets (i.e. sensor errors). According to Habib et al. (2001), the tipping bucket suffers from accuracy problems at high rain rates: it is usually unable to give an accurate estimate of the peak values within the event. This is mainly due to the high gradient of the rain rates at the peaks and valleys of the rainfall time series.

To look for possible identical features in all ERE, the same extraction algorithm is applied on an additional data set from primary stations and stand-alone raingauges owned by national weather services or agencies of WASCAL member countries. This daily rainfall dataset is retrieved from archives of manual ordinary rain gauges dating back in 1960s (Salack et al., 2016) and updated for 2013–2016. The inter-annual variability of seasonal 99th percentile threshold values of INT depicted over 1960–2016 is illustrated by Fig. 3. The latter shows an increasing trend of extreme rainfall thresholds with the recent years' features being similar to the early 1960s. Meanwhile, the inter-decadal variation of these events, depicted by the blue curve, shows that the recent recovery of rainfall is mainly explained by the rain rates of extreme events. These results show that the amplitude, of the thresholds defining heavy rain events, has increased in the recent years. In other words, the amplitude of thresholds defining extreme rainfall has increased. This is similar to arguments provided by Lodoun et al. (2013), Sanogo et al. (2015), Salack et al. (2015), and Maidment et al. (2015) among others. Meanwhile, remote sensing data analysis has also shown that the frequency of extreme rainfall has also increased since the 1980s (Taylor et al., 2017) As this new development of the Sahelseasons is full of challenges for all practitioners, the question is "which type of ERE should be monitored and at what period of the season?"

To answer this question, we developed an *areal* classification scheme for DTO and INT of historical (1960–2016) and multiple sites' daily data (Fig. 1). The extracted DTO (here the DTO unit is converted from day-of-year to week-of-year, WOY, to reduce signal-to-noise ratio) and INT (mm/day) of all observed EREs are subjected to an unsupervised clustering algorithm that groups data based on the Euclidean distance across sample elements in order to find common patterns. The general procedure is to search for a *K-partition* with locally optimal within-cluster sum of squares by moving points from one cluster to another (Hartigan and Wong, 1979). As we have to specify the number of clusters to be used to group the data, we computed the percent variance explained as a function of a possible number of clusters ranging from 2 to 15. The first two clusters explain the maximum, followed by the 3rd, the 4th and so on until the marginal gain drops, giving an angle in the scree plot. The number of clusters is chosen at this point of the scree plot (also called the "elbow"). Once the optimum number of clusters is chosen, clusters centroids are calculated iteratively by reassigning data points, ordered by their distances to the overall mean of the sample, till the within-cluster variation cannot be reduced any further. The within-cluster variation is calculated as the sum of the Euclidean distance between the data values and their respective cluster centroids which correspond to the mean values assigned to each cluster (Hartigan and Wong, 1979). The output of this analysis yielded three categories of INT and two classes of DTO for ERE as described below.

4. Classification of heavy rain rates

The Sahel is characterized by a long dry season followed by a unique rainy season peaking in July–August and retreating in September. The spatial distribution of total annual rainfall decreases as one moves northward from ~1 300 mm to 100 mm (Fig. 1), and it is mainly concentrated over a short period of 3–4 months. The organized mesoscale convective systems, also known as squall lines, contribute the majority of the seasonal rainfall totals (Bell and Lamb, 2006; Smith et al., 2012; Taylor et al., 2017). The natural factors affecting the intra-seasonal variability of the rainfall regime in the Sahelwere summarized in Salack et al. (2016): the local forcing of the Saharan dry air masses, pollution aerosols and regional scale circulation features including the latitudinal movement of the intertropical convergence zone (ITCZ), the Saharan heat low (SHL), the variability of lower-to-upper-tropospheric circulation features such as the African Easterly Jet (AEJ), the Tropical Easterly Jet (TEJ), the African easterly waves and other low-level westerly jets. The global oceans also play a major role in modulating the seasonal

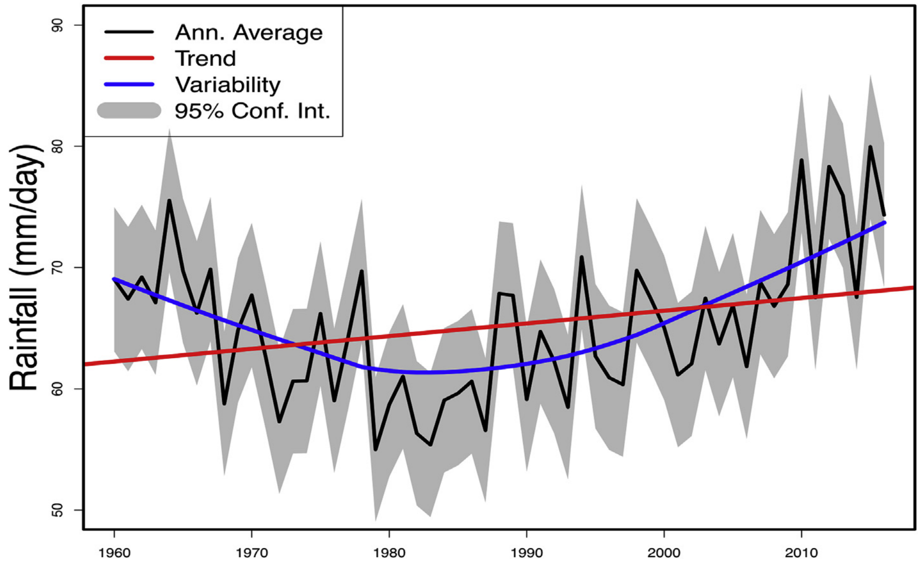

Fig. 3. Inter-annual variability of 99th percentile thresholds of intense rainfall events depicted from 72 stations distributed over the Sahel.

rainfall (Giannini et al., 2013; Salack et al., 2016). The coexistence and interactions of these dynamic processes, with ever changing local land use/land cover types, determine the dominant weather in a season and its associated extreme events. Beside the interannual and interdecadal variability (Lebel and Ali, 2009; Salack et al., 2015), rainfall has been dominated by a high intra-seasonal distribution of sub-daily rainfall intensity (Zahiri et al., 2016) and a high variability of daily events observed in the form of mixed dry/wet patterns (or hybrid rainfall regime) attributed to global and regional warming rates (Salack et al., 2016). While the distribution of events is mainly concentrated within the June–September period, the seasonal total rainfall results from some 40–50 rainy events of which only 2.5%–4% can be considered extreme events (Panthou et al., 2014).

In the Sahel, extreme rainfall events contribute ~50–90% to the seasonal rainfall amount with a South-North gradient (Ta et al., 2016). Table 2 provides the three intensity classes of ERE observed in the Sahel region on a weekly time scale. As provided by the unsupervised K-means clustering, the two categories of DTO reveal the timing of each of the three INT categories. Categories 1 & 2 occur most likely between week 27 and 35 of the year (1 July to 31 August) with an accumulated daily amount varying across 37–65 mm for category 1 and greater than 65 mm/day, but less than 85 mm/day for category 2. The daily accumulated rain rate of category 1 has 52% probability of occurrence against 40% probability for category 2, within the same period. When an extreme rainfall event of category 1 (category 2) is observed from near-surface raingauges or predicted, a yellow (orange) color flag is suggested in operational warning messages. Category 3 is identified when rain rates exceed 85 mm/day, occurring between the 28th and 38th week of the year (10 July to 22 September). It is the most damaging class of heavy rains but very difficult to predict. For operational warnings, ERE of category 3 is flagged with red color denoting highest level risk of flooding or damages. The timing of the three categories of ERE (Fig. 4) falls within three phases of the West African monsoon namely the installation phase (July, 27th −31st week-of-the-year), the intensification phase (August, 31st – 35th week-of-the-year) and the retreat phase (September, 35th – 39th week-of-the-year). Category 1 is observed in the installation phase over central sub-regions after the abrupt monsoon jump (Sultan and Janicot, 2003) while categories 2 & 3 are recorded in the intensification and retreat phases respectively. In these last two phases, rainfall intensity is characterized by a steady increase until it reaches its maximum at the end of August (also known as the continental phase of West African monsoon) and an abrupt retreat in one month, with residual rainfall in October (Lebel and Ali, 2009). The spatial distribution of DTO of Category 2 & 3 suggests an east-west *bipolar* pattern while category 1 is unevenly observed all over the region. All categories are recorded with a time lag of at least one week and the western Sahel is predominantly influenced by the occurrence of categories 2 & 3 in September. The distribution of DTO also exhibits a coherent sub-regional high risk zones of local extreme rainfall discussed below.

Table 2
Categories of intense rainfall events and flag colors for operational warning services.

Category	Parameter	Average	Confidence interval	Proportion (%)	Flag color
Category 1	Intensity (mm/day)	47	[37; 65]	52	Yellow
Category 2	Intensity (mm/day)	75	[65; 85]	40	Orange
Category 3	Intensity (mm/day)	120	> 85	8	Red

5. High -risk areas

The cumulative rainfall of extremely wet days and the maximum number of consecutive wet days have been increasing since the late 1980s, indicating that extreme rainfall events have become more frequent in the West African Sahel during the last decade (Ly et al., 2013; Taylor et al., 2017). The three INT categories of ERE identify the types of local extreme rainfall. Computing the relative frequency of ERE at individual locations enables the identification of areas potentially affected by heavy rain events. Fig. 5 shows the percent probability of occurrence of daily accumulated rain rates of each category. It appears that the northern Sahel stations are highly exposed to category 1 rainfall types with specifically higher potential exposure of eastern and western corners of the sub-region. The southern parts are more likely exposed to category 2 of ERE types at a quasi-equal percent probability of occurrence as category 3 in the southern and western sub-regions. Category 2 may occur everywhere in the Sahel at equal probability of occurrence, only its timing is different from one location to another as illustrated in Fig. 4.

In these arid and semi-arid regions of West Africa, ERE are important sources of impact for life and property and also important sources of water bodies used for multiple purposes including domestic,

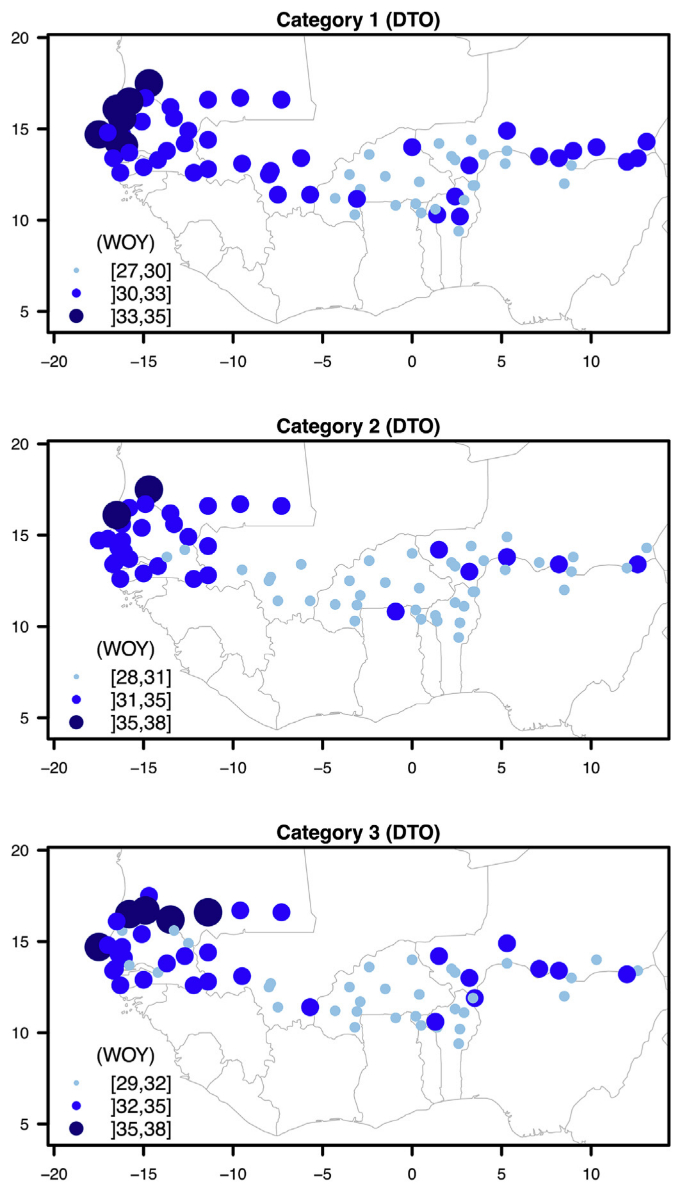

Fig. 4. Intra-seasonal date-of-occurrence (DTO) of extreme rainfall categories (category 1, 2 & 3) expressed in week of a calendar year (WOY).

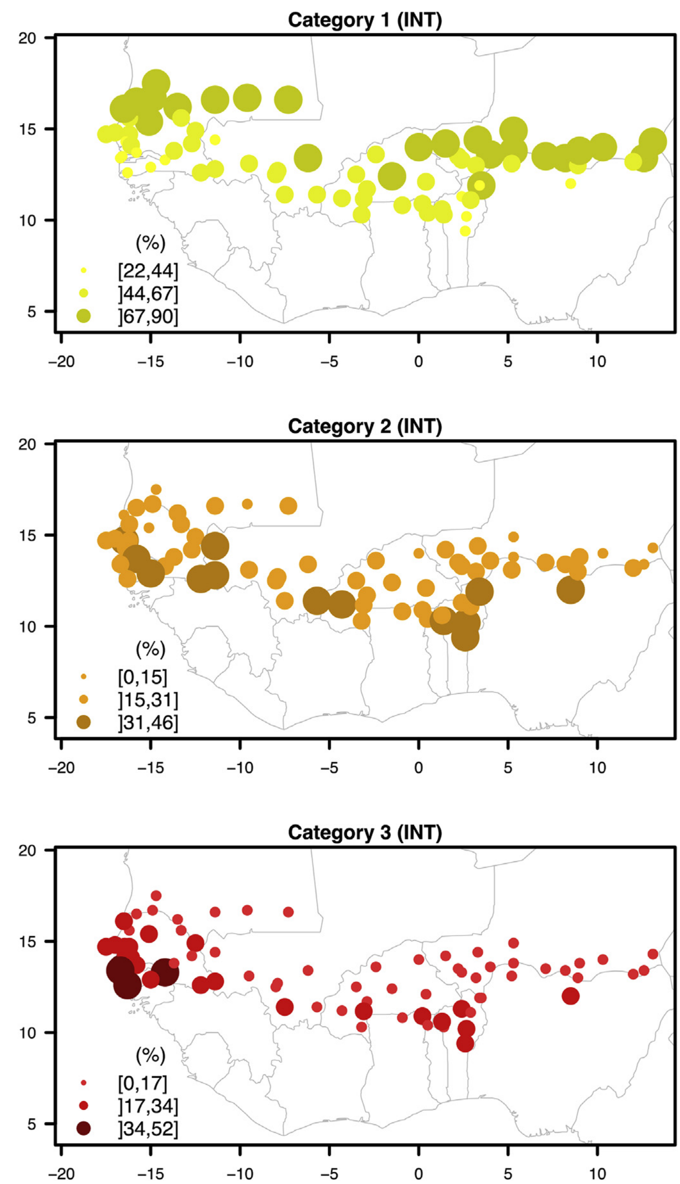

Fig. 5. Relative percent probability of occurrence of extreme rainfall categories (category 1, 2 & 3) per station.

irrigation, fishing, livestock breeding etc. Thus, knowing the spatial distribution of these classes of ERE is valuable to the identification of high risk areas or hot spots which in turn is a crucial input to vulnerability/risk assessments and mapping at all scales (Asare-Kyei et al., 2015).

6. Discussion and conclusions

West Africa is frequently exposed to multiple hydro-meteorological hazards at different scales (Asare-Kyei et al., 2015), notably extreme dry spells, intense rainfall, floods, droughts, air pollution, heat waves, wildfire, etc. Global warming likely increases the frequency and intensity of these extreme events (Sylla et al., 2015; Taylor et al., 2017) or a mixture of some in a unique season/location (Salack et al., 2016). A recent Climate Risk & Early Warning Systems (CREWS) analysis shows that West African countries are most vulnerable to weather extremes because often they have the lowest early warning capabilities, weak or non-existent dissemination systems, and lack of effective emergency planning in case of alerts and warning information (http://newsroom.unfccc.int/media/454810/crews-presentation.pdf). Therefore, all adaptation measures that will spur our population to build resilience rely on the ability of climate information producers to monitor and predict EREs.

99^{th} percentile thresholds are relatively high rain rates whose amplitudes are increasing (see Fig. 3). With respect to the regional marginal soils, land use/land cover types and other vulnerability potentials, peaks above 99th percentile thresholds will always be drivers for flooding, strong run-off and others hazards. When a daily amount, INT, of a given ERE is greater than or equal to 37 mm but less than 65 mm, it should trigger a yellow flag warning especially in the north eastern and western corners of the Sahel. This region is semi-arid with fragile pastoral ecosystem, degraded soils, vulnerable farming systems and people. When the INT is rated above 65 mm/day but below or equal to 85 mm/day, it should be flagged with an orange color denoting a mild level of warning for potential flooding and other damages. The red color flag is waved when INT is estimated above 85 mm/day. This is the highest level of warning which should trigger local disaster management plans. These classes of ERE values, upscaled to week-of-the-year (WOY), solves the problem of rating heavy rains at event scale (Zahiri et al., 2016) in support of monitoring and early warning services. They represent the highest amounts of daily rainfall recorded during a typical rainy season, are much better than the thresholds extracted from 90th percentile as suggested by Ta et al. (2016) which includes average values less than 20 mm/day. Additional observed threshold values of extreme rain events are available for inter-comparison in Salack et al. (2018).

These classes of rain events can have devastating effects on the livelihoods of vulnerable population, crop production, energy management and consumption and biodiversity. The projected increase in climate variability as a result of climate change is expected to increase the risk of these hydro-climatic hazards in the region (Salack et al., 2015; Asare-Kyei et al., 2017). However, the readiness and reaction of national disaster management agencies and civil society organizations to these disastrous hazards have been hampered by inadequate event and vulnerability data collection, assessment, and information sharing which restrict their capabilities for effective disaster management. These rating scales can support better planning and prevention actions by disaster risk managers in the Sahelsub-regions. Likewise, as substantial discrepancies are found among re-analyses and climate model outputs, indicating considerable uncertainties regarding their simulation of extremes (Sillmann et al., 2013; Giannini et al., 2013; among others), downplaying the overall performance of forecasts and climate projections. The rating scales suggested by this study are prominent in operational forecasts verification and climate model output diagnostics and evaluations in terms of timing and amplitude of extreme rainfall events (Salack et al., 2018).

Conflicts of interest

The authors declare no competing interests regarding the publication of this paper.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.wace.2018.05.004.

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