

Article

Quantifying Vegetation Responses to Rainfall Extremes in Sub-Saharan Africa Using CHIRPS Precipitation and MODIS NDVI

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Highlights

What are the main findings?

- We developed a modified heavy rainfall index (mR95pT) that reduces wet-season dominance and improves event-scale detectability across SSA/SAT.
- Using data from CHIRPS (1981–2022) and MODIS NDVI (2003–2022), we found that heavy rainfall can increase vegetation stress (VCI) even under near-normal wetness ($SPI-3 \approx 0$), reaching $\geq 35\%$ in Eastern Africa and $>30\%$ in the Sahel when $mR95pT > 1.0$.

What are the implications of the main findings?

- The proposed index and probabilistic framework enable consistent monitoring of both drought- and heavy-rain-related vegetation stress over large, data-sparse semi-arid regions.
- These results support climate-resilient agricultural and environmental management by identifying conditions under which heavy rainfall elevates vegetation stress risk beyond drought-only assessments.

Abstract

Rainfall variability strongly governs vegetation dynamics in the Semi-Arid Tropics (SAT) of Sub-Saharan Africa (SSA). Yet the impacts of heavy rainfall are less well quantified than those of drought. This study proposes a modified heavy rainfall index (mR95pT) to enable robust comparison of extreme rainfall signals across seasons and regions. The index mitigates the strong seasonal background signal inherent to constant-threshold approaches and highlights episodic heavy rainfall events more clearly. Using CHIRPS precipitation (1981–2022, to derive long-term climatological means) and MODIS NDVI (2003–2022) aggregated to 0.05° and 16-day intervals, we computed the cumulative precipitation, the original ETCCDI-based index (R95pT), and mR95pT across three subregions (Sahel, Southern Africa, and Eastern Africa) and examined event-scale detectability. mR95pT reduced spurious concentration around climatological wet-season peaks and more clearly captured episodic events (e.g., cyclone-related extremes). The vegetation stress (VS) responses were quantified based on the Vegetation Condition Index (VCI) and a probabilistic framework conditioned on background wetness (SPI-3) and heavy rainfall intensity (mR95pT). Under near-normal wetness ($SPI-3 \approx 0$), the baseline VS probability was 18% in Eastern Africa and 13% in the other regions. Conditioning on heavy rainfall increased VS probability (relative to the $SPI-3 \approx 0$ baseline) by +0.8 to +38% (Eastern Africa), +0.6 to +24% (Southern Africa),



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and +11 to +39% (Sahel), with the additional effect diminishing under very wet conditions. Overall, mR95pT and the proposed probabilistic framework provide a scalable pathway to monitor both drought- and heavy-rain-related vegetation risks over data-sparse semi-arid regions.

Keywords: Climate Change Indices; heavy rainfall index; Standard Precipitation Index; Vegetation Condition Index; Semi-Arid Tropics

1. Introduction

Extreme weather events have caused severe impacts on food production, biodiversity, and ecosystems worldwide. These events—defined as statistically rare occurrences of unusually high or low intensity relative to long-term climatology [1]—are particularly damaging in the Semi-Arid Tropics (SAT) of Sub-Saharan Africa (SSA), one of the most vulnerable regions globally. In this region, rainfall variability strongly governs vegetation dynamics [2,3]. Consequently, drought has been among the most frequently studied extreme events [4–6]. In contrast, although the frequency and intensity of heavy rainfall events have been increasing across SSA/SAT, their impacts remain comparatively under-explored [1,7]. A better understanding of both rainfall extremes—drought and heavy rain—is crucial for assessing vegetation conditions and mitigating damage caused by climate extremes.

Numerous indices have been developed to quantify weather anomalies and vegetation responses [8–10]. Standardized indices for precipitation and temperature enable consistent communication and comparison across regions [8]. For instance, several studies examining heavy rainfall have utilized the 27 Climate Change Indices (CCIs) recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) [8,9]. These indices capture long-term trends in the frequency and intensity of extreme events. However, for the SAT—spanning vast, seasonally diverse areas—comparisons across regions remain difficult because differences in climatic zones and seasonal cycles complicate the identification of the timing and location of extreme rainfall events. In strongly seasonal SAT regions, a year-round constant threshold can be dominated by the climatological wet-season peak, making it difficult to highlight episodic, unseasonal heavy rainfall events by using the original heavy rainfall index (R95pT) in CCIs.

Vegetation conditions in SSA are tightly linked to rainfall patterns. Correlation-based analyses between rainfall and vegetation indices often describe these relationships well, particularly for persistent anomalies such as droughts [8,9]. However, such correlations alone are insufficient to capture vegetation responses to short-lived heavy rainfall. Extreme rainfall events may cause both immediate and delayed effects on vegetation: excessive soil moisture, flooding, or surface runoff can negatively impact plant growth [7,11,12], whereas temporary increases in soil water availability can have positive effects [13–15]. In semi-arid ecosystems, these contrasting responses complicate the detection of vegetation degradation caused by heavy rainfall [16]. Therefore, analytical methods that capture both the timing and the strength of vegetation responses—beyond simple correlations—are essential for understanding the complex interactions between rainfall extremes and vegetation dynamics [13,17].

This study aims to quantitatively assess how extreme rainfall conditions—both drought and heavy rainfall—modify vegetation stress in the Semi-Arid Tropics (SAT) of Sub-Saharan Africa. To enable inter-seasonal and inter-regional comparison across the African continent, we first developed a modified heavy rainfall index (mR95pT) based on the original R95pT in the ETCCDI-recommended Climate Change Indices (CCIs). The

proposed index normalizes precipitation accumulated on heavy rainfall days relative to the long-term mean precipitation for the same period, allowing consistent comparisons across regions with distinct rainfall regimes. We then evaluate vegetation responses to drought and heavy rainfall using Earth Observation datasets. The Vegetation Condition Index (VCI), derived from NDVI, is used to identify periods of vegetation stress (hereafter referred to as “VCI droughts”) and to examine meteorological conditions before and during these events. Finally, we apply an event-scale, probabilistic framework to quantify how heavy rainfall is associated with changes in vegetation stress likelihood while controlling for background wetness using the Standardized Precipitation Index (SPI-3). This is particularly important because heavy rainfall can elevate vegetation stress risk even under near-normal seasonal wetness, which drought-only metrics cannot capture.

2. Materials and Methods

2.1. Study Area

The analysis domain covers 40°N–40°S and 20°W–55°E over the African continent (Figure 1). The study focused on the Semi-Arid Tropics (SAT), defined using the Köppen aridity index (AIK), computed from long-term precipitation and temperature variables (see Section 2.3 for datasets and pre-processing). Grid cells classified as semi-arid (AIK = 5.7–13.6) were retained [18], while this criterion excluded the Sahara Desert and North Africa. For descriptive purposes, we further grouped the SAT domain into three subregions (Sahel, Eastern Africa, and Southern Africa) following the boundaries shown in Figure 1.

$$\text{Köppen Arid Index} = \frac{\text{Mean Precipitation}[\text{mm}]}{\text{Mean Temperature}[\text{°C}]} + 33 \quad (1)$$

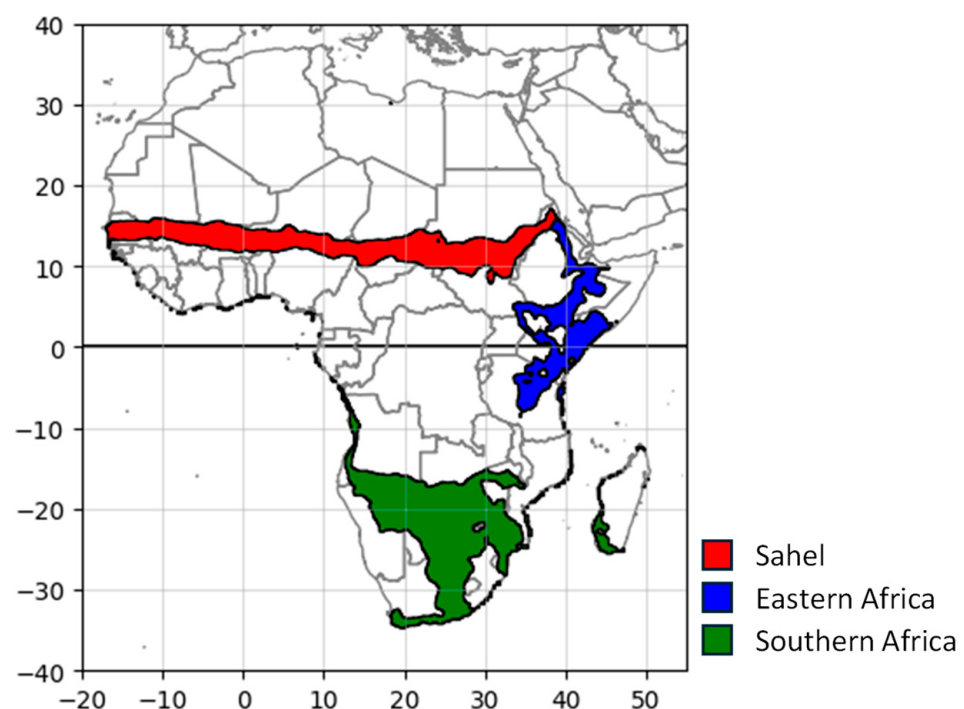


Figure 1. Analysis area of the Semi-Arid Tropics (SAT) used in this study, with three subregions in Sub-Saharan Africa (SSA).

The main land cover classes are savanna, grasslands, and croplands. Annual herbaceous species particularly occur in natural vegetation. Major crops such as maize, millet, and sorghum are grown during the wet season and cultivated before the dry season.

2.2. Procedures of Precipitation–Vegetation Response Analysis

Figure 2 shows the procedure of this study, from the pre-processing of the used data and the calculation of indices related to precipitation and vegetation to the evaluation of vegetation responses to extreme rainfall events.

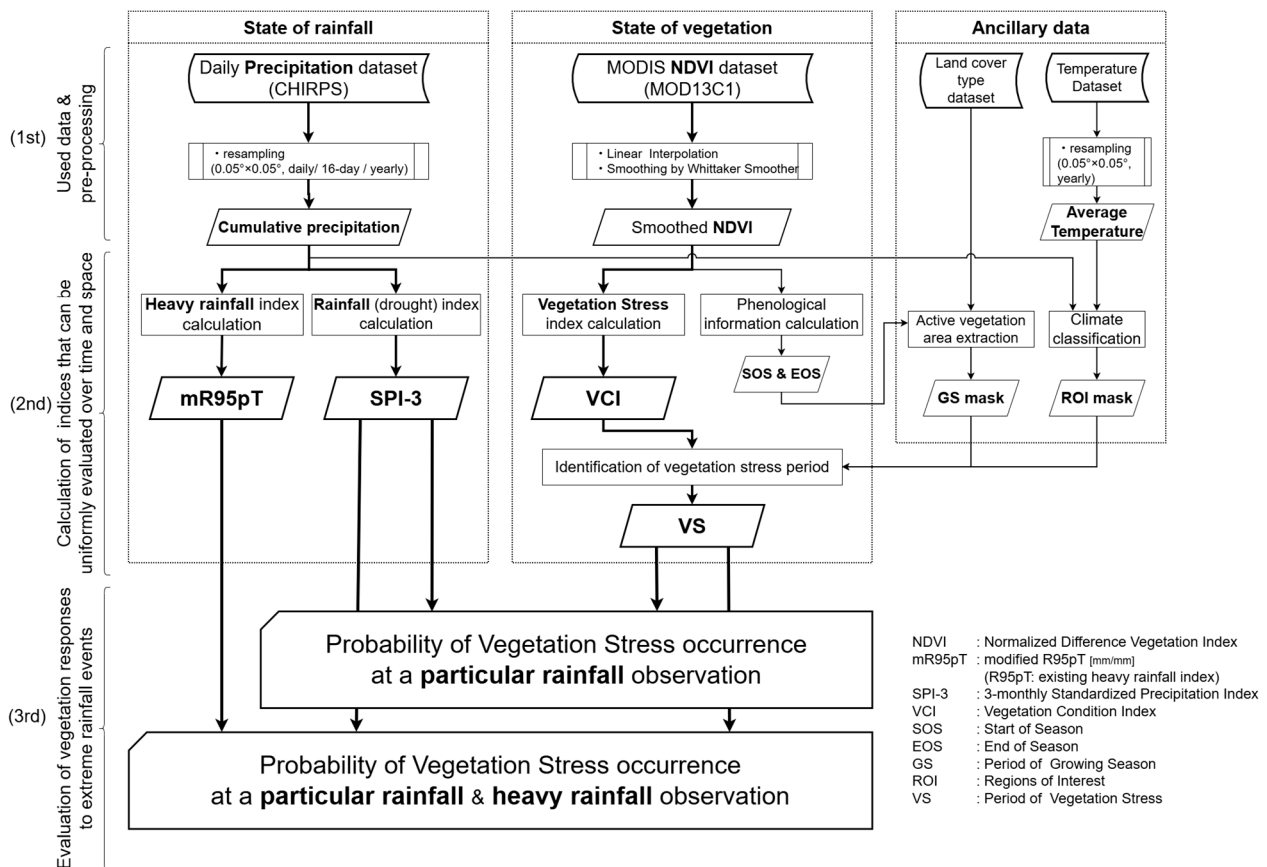


Figure 2. Procedures of seasonal and regionally comparable precipitation–vegetation response analysis in Sub-Saharan Africa. (Dotted lines indicate the different data used and its process. See Section 2.3).

First (1st), Earth Observation datasets based on remotely sensed data were obtained and pre-processed (2.3). The precipitation dataset was used to assess rainfall conditions, and the NDVI dataset was used to understand vegetation responses. These datasets were preprocessed to a spatial resolution of 0.05° (~5 km) and temporal resolutions of daily, 16-day, and yearly. Ancillary datasets were also used to extract the region of interest. The land cover type dataset was used to extract the active vegetation area. The temperature dataset was used to classify the climate along with annual precipitation.

Second (2nd), we calculated and normalized the indices that can be uniformly evaluated over time and space (2.4). The heavy rainfall index (mR95pT), a modified version of the indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI), was developed to meet these requirements. The 3-monthly Standard Precipitation Index (SPI-3), widely used as a drought index, was adopted to express cumulative precipitation over 3 months. Vegetation stress is defined as a vegetation condition worse than the average year and is identified when the Vegetation Condition Index (VCI) falls below a threshold during the growing season. VCI, which represents the health of ground vegetation, was calculated by normalizing NDVI relative to the maximum and minimum values for the same period in previous years. The growing season was identified from the NDVI time series.

Lastly (3rd), we evaluated vegetation responses to extreme rainfall events by assessing the probability of vegetation stress occurrence when specific weather conditions were observed (2.5). When assessing the effects of a lack of rain, only SPI-3 conditioning was used. This is because cumulative precipitation strongly influences plant growth, and other factors can be approximated for the time being. When evaluating the effects of heavy rain, mR95pT and SPI-3 conditioning were used. This is because heavy rain increases the water available to plants, so the impact of cumulative precipitation must be removed. This probabilistic formulation allows us to quantify the effects of events on vegetation while controlling background wetness conditions.

Details of the data processing are described in the following sections.

2.3. Used Data

2.3.1. CHIRPS Daily Precipitation Dataset

The Climate Hazard Group Infrared Precipitation with Stations (CHIRPS) dataset is a precipitation grid dataset provided by the University of California, Santa Barbara [19]. CHIRPS is a high-resolution rainfall product that combines infrared-based precipitation estimates with in situ station observations. It uses Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis version 7 (TMPA 3B42 v7) to calibrate cold-cloud-duration rainfall estimates and blends station data to produce the final gridded precipitation fields. This dataset is widely used for drought detection and trend analysis.

It has a spatial resolution of 0.05° and a daily temporal resolution covering 50°S to 50°N . CHIRPS provides a multi-decadal precipitation record from 1981 onward. In this study, we used CHIRPS daily precipitation for 1981–2022 to compute precipitation-based indices (mR95pT and SPI-3) and to derive long-term climatological means and thresholds.

2.3.2. MODIS NDVI Dataset

MOD13C1 is derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data and has a spatial resolution of 0.05° and a composite interval of 16 days to remove effects such as cloud cover [20]. It provides vegetation indices (Normalized Difference Vegetation Index: NDVI, Enhanced Vegetation Index: EVI) and a QA flag, etc. MODIS NDVI products are available from 2000 to the present; however, this study uses the 2003–2022 period for the analyses (see Section 2.4.3). NDVI is highly correlated with vegetation coverage and is widely used as an indicator of plant activity. To capture vegetation dynamics, pixels with QA flags other than 0 or 1 were linearly interpolated from the NDVI data using values from preceding periods and then smoothed with the Whittaker Smoother [21] with parameters $d = 2$ and $\lambda = 5000$. Because the subsequent analyses use 16-day composites and subregional statistics, the results are insensitive to moderate variations in smoothing strength; we therefore adopt this standard parameterization for MODIS NDVI time-series smoothing. The VCI at the start of season (SOS) and the end of season (EOS) was calculated using multi-temporal NDVI to assess vegetation conditions and phenology.

2.3.3. Ancillary Data

MCD12C1 is a land cover classification dataset created by MODIS and has been provided annually since 2001 for the entire globe at a spatial resolution of 0.05° [22]. In this study, to extract target pixels for vegetation response analysis using VCI, non-vegetated area classes were masked using the International Geosphere and Biosphere Program (IGBP) classification scheme.

CPC Global Temperature is a daily minimum/maximum temperature gridded analysis dataset provided by the NCEP/Climate Prediction Center, covering the globe at a spatial resolution of 0.5° and a temporal resolution of 1 day [23]. It is recommended to use the average of the daily minimum and maximum temperatures as the daily mean temperature.

In this study, to identify semi-arid regions using the AIK, we linearly resampled the data to a 0.05° spatial resolution and computed the mean temperature over 16 days.

Named cyclone events and the desert locust upsurge mentioned in Section 3 are provided solely as contextual references based on publicly available situation reports and summaries [24–28] and were not used as inputs to the index calculation or probabilistic analysis.

2.4. Calculation (Normalization) of Indices

2.4.1. Modified Heavy Rainfall Index: $mR95pT$

A “heavy rain day” is defined as a day with daily precipitation (RR) exceeding a threshold. Heavy rainfall is quantified using $R95pTOT$, one of the 27 Climate Change Indices (CCIs) recommended by ETCCDI. Following ETCCDI, wet days are defined as days with $RR \geq 1$ mm.

Let j denote an analysis period consisting of n consecutive days and let t denote the day of year (DOY). We first describe the original ETCCDI definition and then introduce our modified index, $mR95pT$, designed for inter-seasonal and inter-regional comparison.

$$R95p_j[mm] = \sum_{k=1}^n P_{jk}, \quad \text{where } P_{jk} > ER_{95} \quad (2)$$

The threshold ER_{95} is defined as the 95th percentile of daily precipitation on wet days during a 30-year reference period (1991–2020). Because ER_{95} is computed from all days in the year, it is treated as a constant threshold throughout the year.

$$ER_{95}[mm/day] = 95\%ile(\{P_{w,t} | P_{w,t} > 0\}) \quad (3)$$

where w is the target year ($1991 \leq w \leq 2020$); $P_{w,t}$ is the daily precipitation amount for the year w ; and day of year (DOY) t ; $95\%ile(\{x\})$ is a function that calculates the 95th percentile value of the set $\{x\}$.

Previous studies [29,30] have also used a normalized index ($R95pT_j$), which divides $R95p_j$ by the total precipitation for the same period j ($PRCPTOT_j$).

$$PRCPTOT_j[mm] = \sum_{k=1}^n P_k \quad (4)$$

$$R95pT_j[mm/mm] = \frac{R95p_j}{PRCPTOT_j} \quad (5)$$

However, when applying these existing indices to SAT across Sub-Saharan Africa, three issues arise. First, indices expressed in mm (or mm/day) are difficult to compare across climatic regions with substantially different rainfall regimes. Second, because SAT has pronounced rainy and dry seasons, a threshold derived from all 365 days can be unsuitable for inter-seasonal comparisons. Third, the conventional normalization $R95pT$ does not directly convey how anomalous heavy rainfall totals are relative to the climatological precipitation amount.

To address these limitations, we propose a modified heavy rainfall index, termed modified $R95pT$ ($mR95pT$), designed to be comparable across regions and seasons at the continental scale. First, a day-of-year-specific heavy rainfall threshold (mER_{95t}) is calculated. The mER_{95t} is defined as the 95th percentile of daily precipitation on wet days within a 15-day moving window centered on day t (i.e., ± 7 days) during the 30-year reference period (1991–2020), corresponding to a maximum sample size of 450 days. Following ETCCDI, wet days are defined as days with daily precipitation $RR \geq 1$ mm. Missing daily precipitation values within the 15-day window across the reference years are excluded

from the percentile estimation, and the wet-day count N is computed from the available wet-day observations after excluding missing values. This approach accounts for seasonal variability in rainfall characteristics. The sensitivity of mER_{95t} to the moving-window length was tested by repeating the threshold estimation with $W = 11, 15$, and 21 days, revealing consistent seasonal patterns when summarized at the subregional scale (median across 0.05° pixels for each day of year, Appendix A.1, Figure A1). The frequency with which the percentile estimate falls below 10 mm was also quantified across N settings and regions with low wet-day counts, supporting the use of $N = 30$ and the 10 mm minimum threshold for stable estimation (Appendix A.1, Table A1). When fewer than 30 wet days are available within the reference window, the percentile-based threshold cannot be robustly estimated. In such cases, mER_{95t} is set to 10 mm, in accordance with the ETCCDI-defined R10mm index.

$$mER_{95t} = \begin{cases} 10 & \text{if } N < 30 \\ 95\%ile(\{P_r | P_r \geq 1\}) & \text{if } N \geq 30 \end{cases} \quad (6)$$

where r is a 15-day moving window centered on day t (i.e., $t - 7$ to $t + 7$), P_r is the 95th percentile daily precipitation amount within 450 days, and N is the number of available wet-day observations ($RR \geq 1$ mm) within the 450-day reference sample (after excluding missing values). Here, “transition-prone conditions” are defined operationally as DOY periods with low N and/or when the 10 mm minimum threshold is applied in Equation (6).

Next, the total precipitation on heavy rain days during period j was calculated, denoted $mR95pj$. A heavy rain day within period j is defined as a day whose daily precipitation exceeds the corresponding mER_{95t} , and $mR95pj$ is obtained by summing daily precipitation over those heavy rain days.

$$mR95p_j[mm] = \sum_{i=1}^n P_{ij}, \text{ where } P_{ij} > mER_{95t} \quad (7)$$

To normalize this quantity in a way that supports inter-regional and inter-seasonal comparison, we compute the climatological (normal) total precipitation for period j , denoted as $\overline{PRCPTOT}_j$ from the same 30-year reference period (1991–2020). Here, period j corresponds to the same n -day analysis interval used throughout the study (16-day intervals), and $\overline{PRCPTOT}_j$ is computed for the corresponding 16-day period j over the reference years.

$$\overline{PRCPTOT}_j[mm] = \frac{1}{30} \times \sum_{w=1991}^{2020} \sum_{i=1}^n P_{wij} \quad (8)$$

where P_{wij} is the daily precipitation on the day i of the period j in the year w .

Finally, $mR95pj$ is normalized by $\overline{PRCPTOT}_j$ to obtain the modified heavy rainfall index $mR95pT_j$.

$$mR95pT_j[mm/mm] = \frac{mR95p_j}{\overline{PRCPTOT}_j} \quad (9)$$

In the rare case that $\overline{PRCPTOT}_j = 0$ for a pixel/period, $mR95pT$ is treated as undefined and the corresponding value is masked to avoid division by zero. This index is dimensionless and represents the ratio of the total precipitation on heavy rain days in period j to the climatological precipitation total for the same period.

2.4.2. Standard Precipitation Index: SPI

The Standardized Precipitation Index (SPI) is a precipitation-based index that quantifies wet and dry anomalies at a given time scale for accumulated precipitation. SPI is calculated by fitting a probability distribution (typically a two-parameter gamma distri-

bution) to accumulated precipitation, converting the fitted cumulative probability to a standard normal variate, and expressing anomalies as standardized z-scores [31]. In this study, we used SPI-3 (3-month accumulation) because vegetation conditions in semi-arid regions are strongly influenced by rainfall accumulated over the preceding several months rather than by single-day events.

SPI-3 was computed for each pixel over the study period (1981–2020). Let $P_{w,j}$ [mm] denote the 3-month total precipitation in year w for period j (12 periods per year). For each pixel and each period j , a two-parameter gamma distribution was fitted to the non-zero samples ($P_{w,j} > 0$) using maximum likelihood estimation:

$$g(P_{w,j}) = \frac{1}{\beta^\alpha \Gamma(\alpha)} P_{w,j}^{\alpha-1} \exp\left(-\frac{P_{w,j}}{\beta}\right), \text{ for } P_{w,j} > 0 \quad (10)$$

where $\alpha > 0$ is the shape parameter, $\beta > 0$ is the scale parameter, and $\Gamma(\alpha)$ is the gamma function:

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \quad (11)$$

The cumulative probability for a given precipitation total $P_{w,j}$ is then obtained from the fitted gamma distribution:

$$G(P_{w,j}) = \int_0^{P_{w,j}} g(x) dx \quad (12)$$

Because zero precipitation can occur, the cumulative probability was adjusted as follows [31]:

$$H(P_{w,j}) = q_j + (1 - q_j)G(P_{w,j}) \quad (13)$$

where q_j is the probability of zero precipitation for period j at the corresponding pixel (i.e., the fraction of years with $P_{w,j} = 0$ during 1981–2020). Finally, SPI was computed by transforming $H(P_{w,j})$ to a standard normal variate:

$$SPI_{w,j} = \Phi^{-1}(H(P_{w,j})) \quad (14)$$

where $\Phi^{-1}(\cdot)$ is the inverse cumulative distribution function of the standard normal distribution.

2.4.3. Vegetation Condition Index: VCI

VCI is commonly used to monitor agricultural drought [3]. In this study, it was used to determine whether plant growth conditions were higher or lower compared to the value in long-term observation. VCI is calculated by normalizing NDVI against the maximum and minimum values observed during the same period in previous years [6,32].

$$VCI_{ij} = \frac{NDVI_{ij} - NDVI_{jmin}}{NDVI_{jmax} - NDVI_{jmin}} \times 100 \quad (15)$$

where $NDVI_{ij}$ is the NDVI observed in year i during period j ; $NDVI_{jmin}$ is the minimum NDVI observed in period j from 2003 to 2022; and $NDVI_{jmax}$ is the maximum NDVI observed in period j from 2003 to 2022.

2.4.4. Phenology and Growing Season

One objective of this study is to quantitatively evaluate extreme drought and heavy rainfall events that impact natural vegetation and agricultural production. To achieve this, it is necessary to identify phenology and crop growing seasons within the study area's veg-

etation zones. In this study, phenological information was extracted from MODIS/NDVI time series (16-day intervals) using TIMESAT3.3. [33]. To accommodate multiple seasons per year, data were smoothed using a Savitzky–Golay filter with a window size of 4 to determine the start of season (SOS) and the end of season (EOS). The growing season (GS) was defined as the period from SOS to EOS.

2.4.5. Detecting Period of Vegetation Stress

In this study, a VCI-based vegetation stress (VS) metric is defined to represent periods of poor vegetation condition (as indicated by VCI). In contrast, agricultural drought is often defined in terms of reduced soil moisture available to vegetation. VS was identified using VCI and phenological information. Following the National Drought Management Authority (NDMA) VCI-based drought classification, $VCI < 20$ was treated as indicating severe vegetation stress. First, during the growing season, periods when VCI was below 20 were assigned $VCI^* = 1$, while all other periods were assigned $VCI^* = 0$.

$$VCI^*_{lat,lon,t} = 1 \text{ if } (VCI_{lat,lon,t} < 20 \text{ and } GS = 1) \\ VCI^*_{lat,lon,t} = 0 \text{ otherwise} \quad (16)$$

where lat and lon denote the latitude and longitude of a pixel, t is the 16-day period, and GS is a binary variable indicating whether the period falls within the growing season. Second, to remove one-period gaps in VCI^* , we applied a simple temporal consistency rule: if $VCI^* = 1$ in both the preceding and following periods ($t - 1$ and $t + 1$), the intermediate period was also set to 1.

$$VCI^{**}_{lat,lon,t} = 1 \text{ if } VCI^*_{lat,lon,t} = 1 \text{ or } (VCI^*_{lat,lon,t-1} = 1 \text{ and } VCI^*_{lat,lon,t+1} = 1); \\ \text{otherwise } VCI^{**}_{lat,lon,t} = 0. \quad (17)$$

Periods where $VCI^{**} = 1$ occurred for three or more consecutive periods were defined as vegetation stress occurrence periods ($VS = 1$), and the latitude, longitude, and start and end dates of vegetation stress occurrence were identified for each pixel. To assess the robustness of the VCI-based VS detection against cloud-contaminated observations, a sensitivity analysis was conducted using MOD13C1 quality flags (Appendix A.2, Figure A2), confirming that 16-day VS pixel counts are consistent across QA screening choices.

2.5. Evaluation of Vegetation Responses to Extreme Rainfall Events

The effects of extreme rainfall events on plant activity levels were evaluated by appropriately setting the temporal scale and causal structure. First, hypotheses were formulated regarding the mechanisms by which each extreme rainfall event affects plant activity over time. Next, the conditional probability of VCI-based vegetation stress occurrence was calculated separately for the regions shown in Figure 1, “Sahel,” “Eastern Africa,” and “Southern Africa”, for periods with and without observed extreme rainfall events.

2.5.1. Probability of Vegetation Stress Occurrence During Low Rainfall Events

The relationship between cumulative precipitation and vegetation condition was assumed to be that precipitation strongly affects vegetation simultaneously (Figure 3). Both variables are also influenced by their own past states. Furthermore, low rainfall (dryness) and vegetation stress often occur simultaneously. To isolate the adverse effect of low rainfall from overall wetness, $P(VS = 1 | SPI - 3 = x_d)$ was estimated using the following formula.

$$P(VS = 1 | SPI - 3 = x_d) \quad (18)$$

where VS denotes binary variables representing the occurrence or absence of vegetation stress in a given period t and x_d denotes average $SPI-3$ during a given agricultural drought occurrence period. It is classified in Table 1.

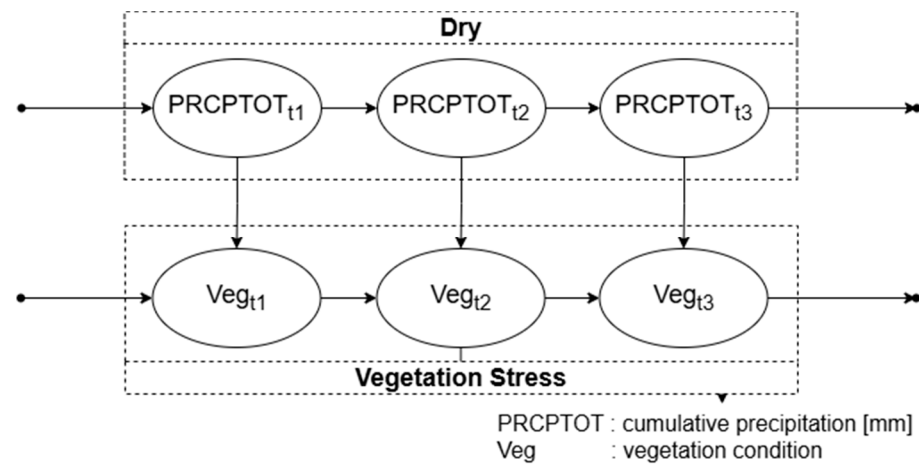


Figure 3. Schematic diagram of the relationship between cumulative precipitation and vegetation condition during a low rainfall event.

Table 1. Class of $SPI-3$.

$SPI-3$	-	-1.5	-1	-0.5	0	0.5	1	1.5	+
x_d	<-1.75	$[-1.75, -1.25)$	$[-1.25, -0.75)$	$[-0.75, -0.25)$	$[-0.25, 0.25)$	$[0.25, 0.75)$	$[0.75, 1.25)$	$[1.25, 1.75)$	≥ 1.75

Because a vegetation stress episode spans multiple 16-day periods, precipitation conditions for each episode were summarized by using the mean $SPI-3$ over the episode and discretizing it into classes (Table 1). Using Bayes' theorem, the $P(VS = 1 | SPI-3 = x_d)$ was estimated, where probabilities are computed as relative frequencies across all periods in the record.

$$\frac{P(SPI-3 = x_d | VS = 1) \cdot P(VS = 1)}{P(SPI-3 = x_d)} \quad (19)$$

$P(SPI-3 = x_d | VS = 1)$ was calculated as the rate of the count of vegetation stress events that satisfied $SPI-3 = x_d$. $P(VS = 1)$ and $P(SPI-3 = x_d)$ were calculated as the rate of periods that satisfied each condition.

2.5.2. Probability of Vegetation Stress Occurrence After Heavy Rain Event

Figure 4 provides a conceptual overview of the hypothesized links among heavy rainfall, background wetness, and vegetation condition in our descriptive framework. Heavy rain not only benefits vegetation by increasing precipitation but also harms it by causing wet damage and landslides. The analysis considers heavy rainfall as an event-scale signal and evaluates its association with vegetation stress, conditional on background wetness, without inferring a synchronous or causal relationship. Therefore, when considering cumulative precipitation, the probability of vegetation stress after a heavy rain event was calculated as follows:

$$P(VS = 1 | SPI-3 = x_w, mR95pT = x_h) \quad (20)$$

where x_w denotes the average $SPI-3$ during a given vegetation stress occurrence period and x_h denotes the maximum $mR95pT$ for the 3 periods prior to the onset of the vegetation stress. Both are classified in Table 2.

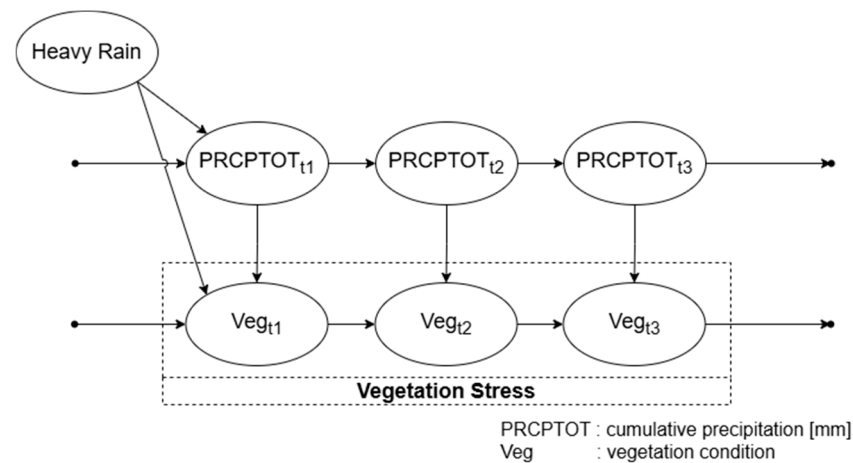


Figure 4. Schematic diagram of the relationship between cumulative precipitation and vegetation condition after heavy rain.

Table 2. Class of heavy rainfall index: mR95pT.

mR95pT	0	0.25	0.75	1.25	1.75	+
x_h	0	[0, 0.5)	[0.5, 1.0)	[1, 1.5)	[1.5, 2.0)	≥ 2.0

Equation (20) was transformed by Bayes' theorem as follows:

$$\frac{P(SPI - 3 = x_d | VS = 1) \cdot P(VS = 1)}{P(SPI - 3 = x_d)} \quad (21)$$

$P(SPI - 3 = x_w, mR95pT = x_h | VS = 1)$ was calculated as the rate of the count of vegetation stress events that satisfied $SPI - 3 = x_w$ and $mR95pT = x_h$. $P(VS = 1)$ and $P(SPI - 3 = x_w)$ were calculated as the rate of periods that satisfied each condition.

Because SPI-3 and mR95pT are both precipitation-derived, we did not assume independence; instead, SPI-3 is used to stratify background wetness conditions, and how the conditional probability of vegetation stress varies with mR95pT within each SPI-3 class (Equation (20)) was evaluated. As a robustness check, Spearman's rank correlation indicates that the residual association between SPI-3 and mR95pT is substantially reduced after stratification (Appendix A.3, Table A2).

The antecedent heavy rainfall exposure was defined as the maximum mR95pT within the 48 days (three 16-day NDVI composite periods) preceding VS onset to align precipitation extremes with the temporal resolution of MODIS NDVI. A sensitivity analysis was conducted using alternative antecedent windows (16, 32, and 64 days) (Appendix A.4, Figure A3).

3. Results and Discussion

3.1. Detection of Heavy Rain Events with Existing and Modified Indices

The modified heavy rainfall index, mR95pT, minimizes the pronounced seasonal background signal present in R95pT, thereby facilitating more precise identification of episodic heavy rainfall events across the SSA/SAT domain. To examine rainfall patterns, cumulative precipitation (PRCPTOT), the existing index (R95pT), and the modified index (mR95pT) were each calculated at 16-day intervals from 1981 to 2022, resulting in 966 periods. Figure 5 illustrates the spatiotemporal variation in these indices in 2019, while Figure 6 depicts temporal variation at three representative sites for 2003–2022, corresponding to the MODIS NDVI/VCI analysis period. The selected sites are Bamako (Sahel), Gaborone (Southern

Africa), and Mogadishu (Eastern Africa). PRCPTOT demonstrates that high-rainfall areas shift from north to south throughout the year. Specifically, SSA/SAT in the Northern Hemisphere shows high values during summer, whereas the Southern Hemisphere shows elevated values in winter, indicating that wet and dry seasons are reversed between the northern and southern SSA/SAT regions (Figure 5, top). Consistent with this, Figure 6(A1–A3) shows these seasonal variations as vertical stripes. R95pT shows a pattern similar to PRCPTOT, with high values particularly evident on the south coast of West Africa during DOY 193–240 and in Southern Africa during DOY 33–80. These periods broadly correspond to the regional wet season (including parts of the cyclone season in some areas), when heavy rainfall events are more likely to occur. Accordingly, Figure 6(B1–B3) also show vertical stripes, mirroring PRCPTOT. These observations indicate that R95pT is strongly dominated by the seasonal precipitation background, and detections tend to concentrate during climatological wet-season peaks.

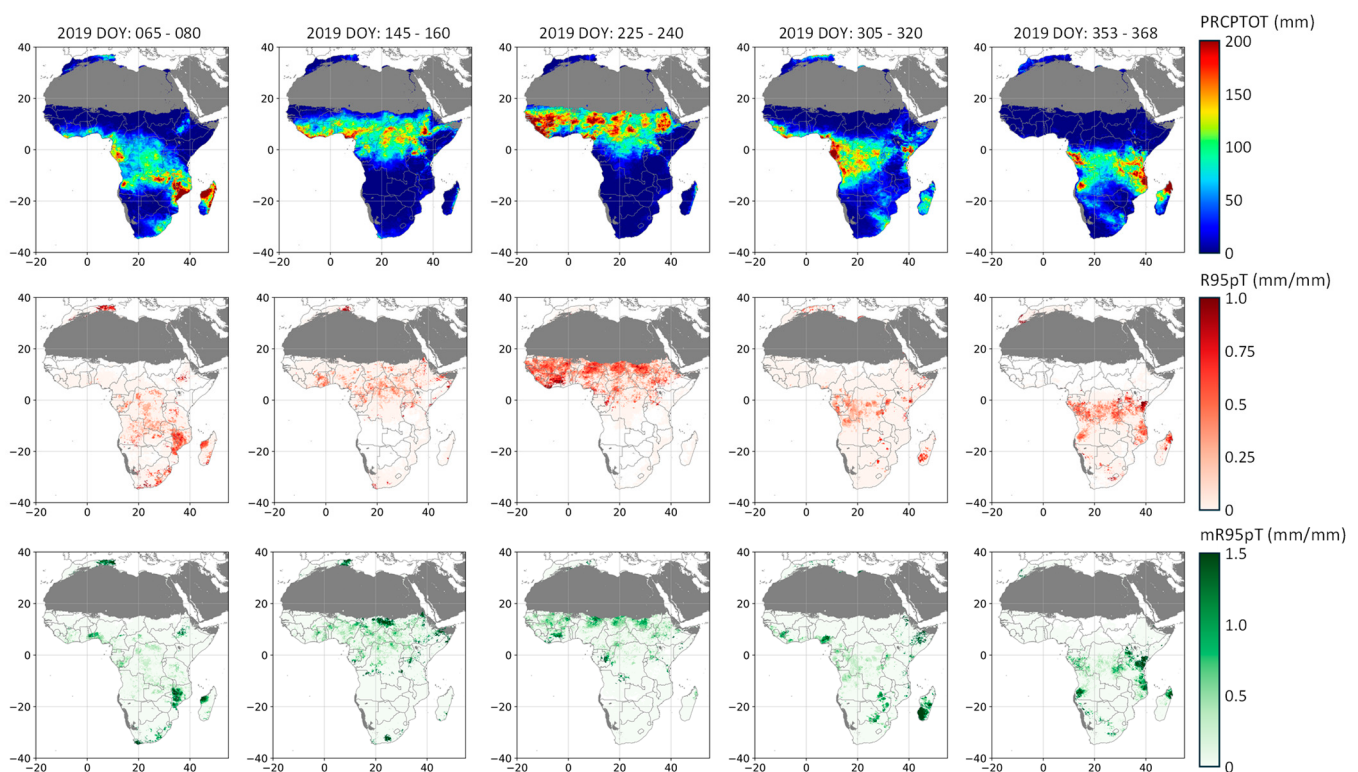


Figure 5. The 16-day total precipitation: PRCPTOT (**top**), existing heavy rainfall index: R95pT (**middle**), and modified heavy rainfall index: mR95pT (**bottom**) within the period of DOY: 065–080, 145–160, 225–240, 305–320, and 353–368 in 2019.

In contrast, mR95pT shows a markedly reduced seasonal background signal, which allows episodic heavy rainfall anomalies to be highlighted more clearly. Consequently, it effectively identifies the episodic anomalies associated with major events, such as the severe cyclone event in March 2019 (over Mozambique, DOY 65–80). Figure 6(C1–C3) further demonstrate that mR95pT reduces seasonal variation and detects events more intermittently.

To further quantify and compare the detection behavior of the two thresholding schemes, we summarized the fraction of pixels identified as “heavy-rainfall” during 2019 for each subregion (Figure 7). This exceedance fraction provides a quantitative indicator of how strongly detections concentrate around the wet-season peak versus highlighting episodic events. The original ETCCDI threshold (ER95), which is defined as a year-round constant, results in an exceedance rate that tends to concentrate during the climatological wet season, consistent with the strong seasonal background signal seen in R95pT

(Figures 5 and 6). Conversely, the day-of-year-dependent threshold (mER95t) moderates this seasonal concentration, yielding a detection rate less dominated by the wet-season peak, allowing episodic events to be highlighted more clearly across regions with distinct rainfall regimes. Building on these distinctions, we next examine areas where detection discrepancies persist.

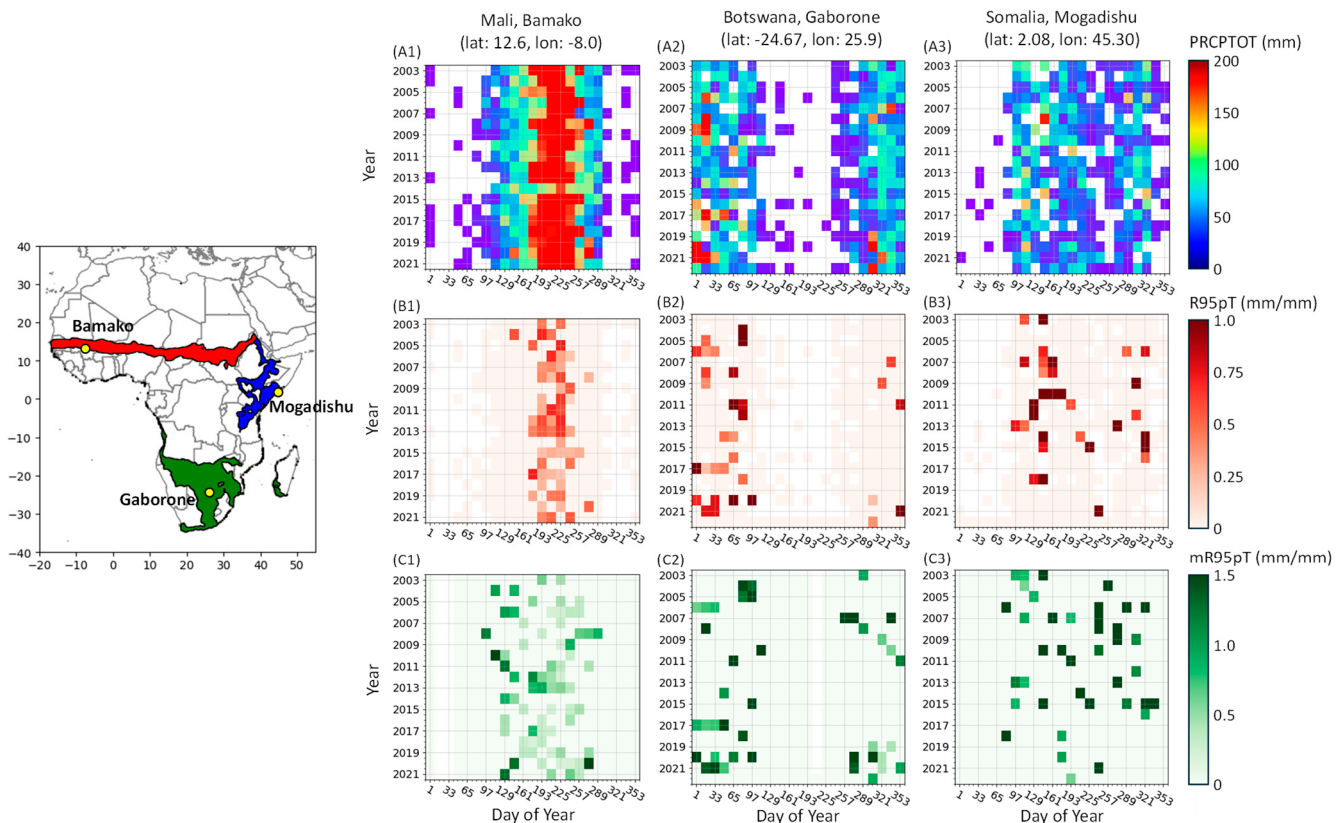


Figure 6. The 16-day total precipitation: PRCPTOT (A1–A3), existing heavy rainfall index: R95pT (B1–B3), and modified heavy rainfall index: mR95pT (C1–C3) in Bamako (Sahel), Gaborone (Southern Africa), and Mogadishu (Eastern Africa) with a 16-day interval from 2003 to 2022.

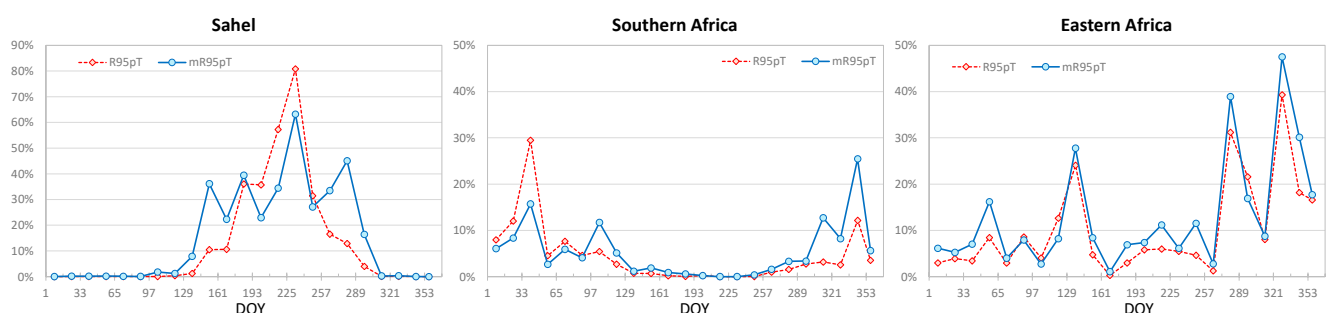


Figure 7. Fraction of pixels classified as heavy rainfall days based on the original constant threshold (ER95) and the day-of-year-dependent threshold (mER95t) in three subregions in 2019. The total number of pixels is 64,781 for the Sahel, 84,555 for Southern Africa, and 34,986 for Eastern Africa.

Sensitivity can be higher around dry–wet transition periods, where the 15-day reference window may include a mixture of wet and dry days and threshold estimation can become more sensitive. This limitation motivates the event-based case studies (Figure 8) and the probabilistic assessment of vegetation stress (Section 3.2). These findings highlight the need to examine transitions further.

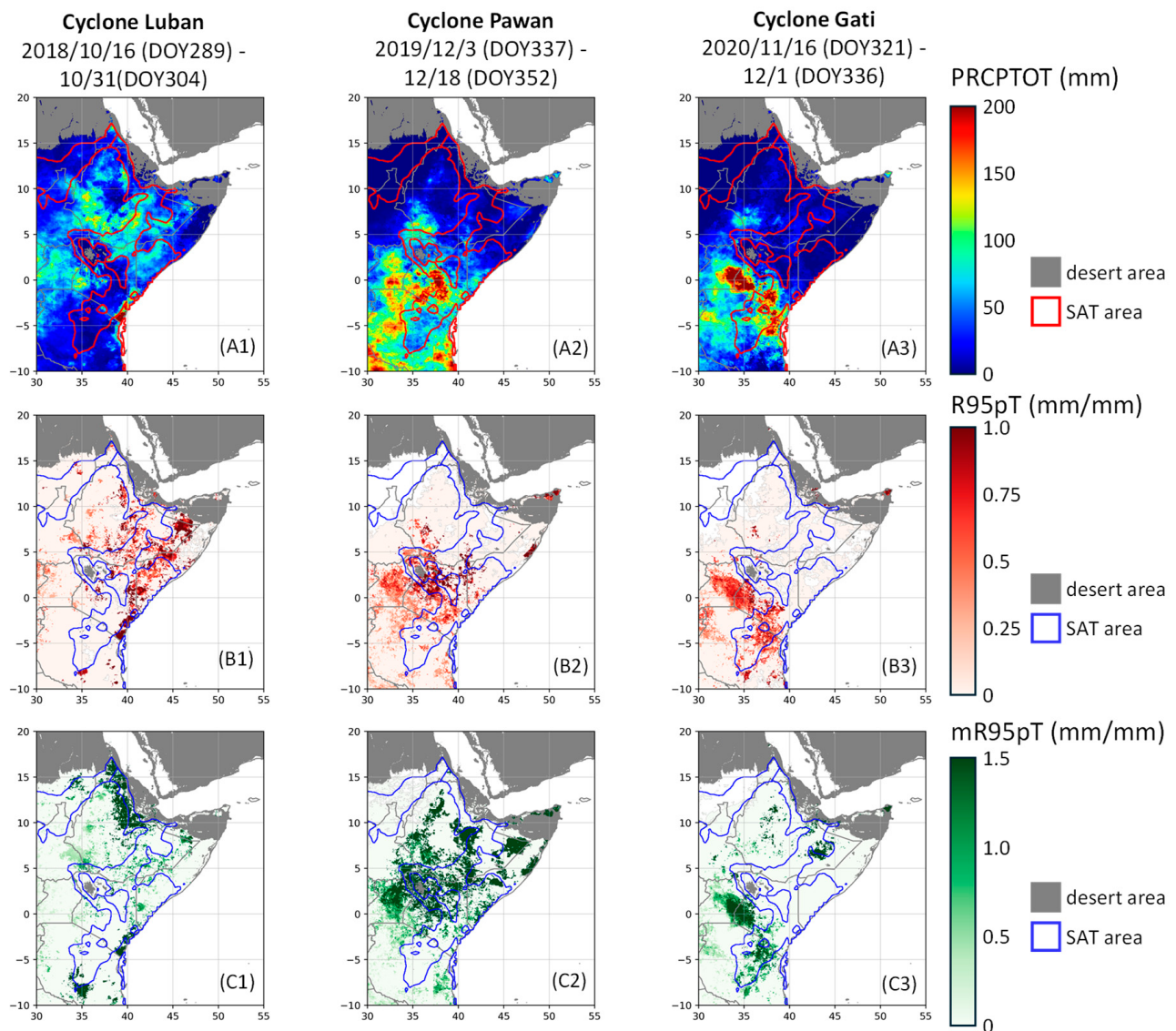


Figure 8. The 16-day total precipitation: PRCPTOT (A1–A3), existing heavy rainfall index: R95pT (B1–B3), and modified heavy rainfall index: mR95pT (C1–C3) during three event periods referenced by publicly reported cyclones (Luban, Pawan, and Gati) that occurred in eastern Africa in 2018, 2019, and 2020. Cyclone names are provided for event context based on public reports [25–28] and were not used as inputs to the analysis.

The seasonal rainfall regimes differ substantially among the three SSA/SAT sub-regions, which helps in interpreting the seasonal patterns in the exceedance fractions shown in Figure 7. In the Sahel, rainfall exhibits a strong boreal-summer peak associated with the seasonal migration of the tropical rain belt (ITCZ), with satellite-based climatology indicating that Sahelian rainfall often reaches its maximum in the second half of August [34]. In Southern Africa, rainfall is predominantly concentrated in the austral summer (roughly October–March), with comparatively dry conditions during the austral winter [35]. In Eastern Africa, precipitation exhibits a bimodal annual cycle in many areas, with “long rains” in boreal spring and “short rains” in boreal autumn, although the spatial pattern is heterogeneous [36].

Consistent with these climatologies, the exceedance fraction based on the original constant threshold (ER95) tends to concentrate around the climatological wet-season peak, particularly in the Sahel (Figure 7). In contrast, the day-of-year-dependent threshold (mER95t) moderates this seasonal concentration. It more frequently identifies exceedances

near the onset and cessation of the rainy season, highlighting episodic heavy rainfall events that may be obscured by the strong seasonal cycle in ER95-based detection. In Eastern Africa, the bimodal, spatially heterogeneous rainfall regime likely contributes to a more complex temporal pattern in the aggregated exceedance fraction, because subregional averaging can mask asynchronous peaks across coastal–inland contrasts and across the Northern and Southern Hemispheres [36]. To illustrate these regional differences at the event scale—particularly under the spatially heterogeneous rainfall regime in Eastern Africa—we next examine several representative heavy rainfall events using both the existing and modified indices (Figure 8). Event names, timing, and affected areas are provided for contextual reference based on publicly available situation reports and summaries [25–28] and were not used as inputs to the index calculation or probabilistic analysis.

The desert locust upsurge from June 2019 to February 2022 posed a significant threat to food production across Eastern Africa, the Arabian Peninsula, and parts of South Asia. This upsurge has been attributed to a sequence of unusually wet conditions and multiple heavy rainfall events, including Cyclone Mekunu, which affected the Arabian Peninsula in 2018 [37] and preceded the 2019–2022 upsurge. Additional heavy rainfall episodes in and around Eastern Africa have also been identified as contributing factors to the persistence and spread of the infestation [38]. In this study, this period is used as a contextual event period to illustrate and compare how the existing index (R95pT) and the modified index (mR95pT) behave during reported heavy rainfall episodes associated with the upsurge (Figure 8). This case study is intended to evaluate rainfall event detectability rather than to attribute subsequent vegetation degradation to locust impacts, which would require pest-specific data and lagged attribution analyses. Figure 8 is presented to aid in the interpretation of event-period index behavior and is not intended as a validation benchmark against cyclone datasets or reported impact on vegetation, agriculture, or livelihoods.

Cyclone Luban hit Yemen and Oman in October 2018 and brought rain to the inland of Sudan and Eritrea [39]. During this period, R95pT detected heavy rainfall mainly in south-west Somalia, whereas mR95pT also showed elevated signals in southern Eritrea during the same period (Figure 8(A1,A2); public reports here are referenced for contextual interpretation only). The unseasonal Cyclone Pawan, which hit Eastern Africa in December 2019, supported the southward migration of locusts [24,26]. R95pT showed elevated heavy rainfall signals mainly in Kenya, while mR95pT highlighted a broader area, including Ethiopia and the eastern coast of Somalia (Figure 8(B1,B2)). Cyclone Gati, which affected Eastern Somalia in November 2020, further intensified locust breeding [27,28]. Both R95pT and mR95pT showed elevated signals during this event period, with mR95pT highlighting a larger spatial extent (Figure 8(C1,C2)). Overall, these event-scale comparisons indicate that mR95pT more consistently captures episodic and potentially off-season heavy rainfall signals than R95pT, particularly around seasonal transition periods when constant-threshold detection can be dominated by the climatological seasonal cycle. Notably, these comparisons focus on the detectability and spatial consistency of rainfall extremes and do not imply a direct causal link between individual events and subsequent ecological or agricultural impacts. This supports the utility of mR95pT for identifying unseasonal heavy rainfall episodes that may be missed or deemphasized by the original ETCCDI-based approach.

The modified heavy rainfall index mR95pT, developed in this study, is intended to facilitate comparison across different regions and seasons. Compared to the existing R95pT index, mR95pT reduced spurious concentration around peak wet-season conditions and improved the detectability of episodic heavy rainfall events outside the climatological wet-season peak. Notably, damaging heavy rain events affecting vegetation frequently occur outside the wet-season peak. Furthermore, because mR95pT is normalized by the average total cumulative precipitation for the same period, it is suitable for analyzing large areas

with heterogeneous climates, such as continental-scale datasets. The index highlighted several societally relevant heavy rainfall periods (including event periods discussed above) and a particularly severe event in South Africa. mR95pT is optimized to highlight episodic heavy rainfall anomalies, which may result in downweighting of widespread, moderate rainfall events. Comprehensive validation of false positives and false negatives would require independent ground-truth data, such as yield records, in situ damage reports, or disaster databases, and is identified as an area for future research. However, mR95pT can be more sensitive around dry–wet transition periods, when threshold estimation may be affected by mixed dry and wet conditions within the reference window. The index modulates detection sensitivity using the mER95t threshold, calculated from daily precipitation on rainy days during the same period in previous wet seasons, whereas a fixed value (10 mm) is used for dry seasons. Since the timing of transitions between dry and wet seasons varies annually, these periods often contain a mix of dry and wet days, resulting in lower threshold values. Refining the threshold-estimation procedure during these transitional periods may improve stability and reduce sensitivity to mixed wet–dry sampling.

In summary, mR95pT reduced the pronounced seasonal background signal present in PRCPTOT and R95pT, thereby enabling more precise identification of episodic heavy rainfall events across regions with varying rainfall regimes. Nevertheless, the index can show heightened sensitivity during dry–wet transitions, likely because the day-of-year threshold (mER95t) can be underestimated when the 15-day reference window includes both wet and dry days. Refining threshold estimation during seasonal transitions is expected to further enhance event detectability. This transition sensitivity suggests that mER95t can be underestimated when the 15-day window includes mixed wet and dry conditions. We therefore evaluate how these rainfall extremes and vegetation stress are evaluated using the probabilistic framework outlined in Section 2.5.

3.2. Evaluation of Vegetation Responses to Extreme Weather Events

3.2.1. Vegetation Stress Probability Conditioned on SPI-3

Figure 9 shows the probability of vegetation stress occurrence at a particular cumulative precipitation level. The cumulative precipitation was expressed as SPI-3, and the probability was defined as the conditional probability $P(VS = 1 \mid SPI-3 = x_d)$. When $SPI-3 = 0$ ($-0.25 < x_d \leq 0.25$), it indicates the probability under normal weather conditions. This probability is 18% in Eastern Africa and 13% in other regions. The effect of a lack of rain on vegetation can be quantified by the probability difference between $SPI-3 = x_d$ and $SPI-3 = 0$. When $SPI-3 = -1.5$ ($-1.75 < x_d \leq -1.25$), the differences were the highest in all regions. These were +29% in Southern Africa, +26% in Eastern Africa, and +13% in the Sahel. When SPI-3 exceeded 0.75, the probability of occurrence was very low (<5%). The probability of vegetation stress increases as SPI3 decreases. This result is consistent with some existing studies that show precipitation and vegetation indices have strong correlations [8,9] and suggests that a lack of rainfall damages vegetation. The probability of change due to SPI-3 is the smallest in Sahel. This suggests that the effect of a lack of rain on vegetation is weaker than in other regions. One possible contributing factor is irrigation, which can buffer vegetation conditions during rainfall deficits, although other factors (e.g., vegetation type, soils, and land use/management practices) may also play a role and are not explicitly analyzed here. The share of cultivated area equipped for irrigation in Sahel is 6.9%, higher than Eastern Africa (2.6%), Southern Africa (4.2%), and the SSA average (3.5%) [38,39].

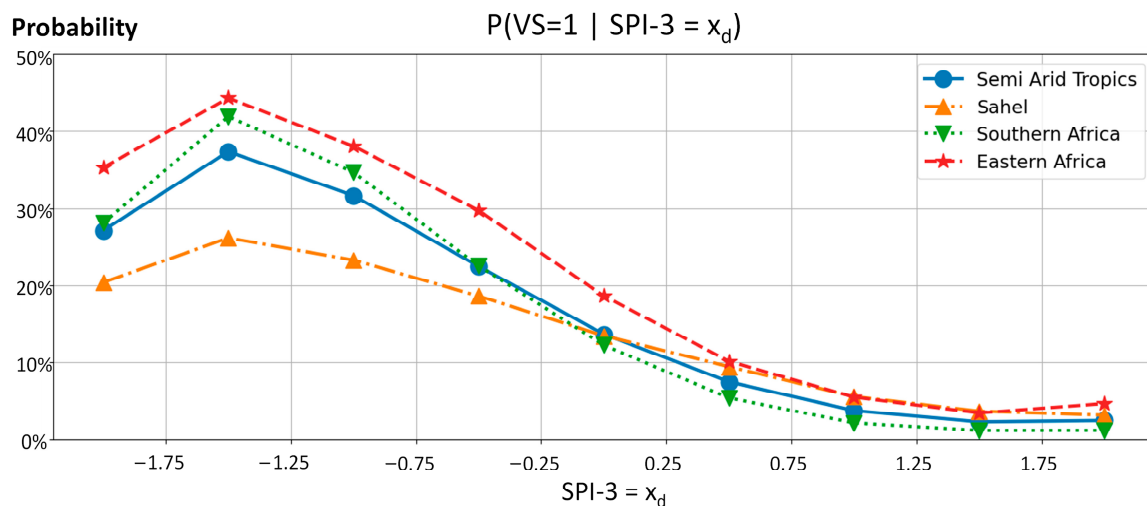


Figure 9. The probability of vegetation stress occurrence at each SPI-3 class.

3.2.2. Additional Effect of Heavy Rainfall Conditioned on SPI-3 and mR95pT

For further quantification, the probability of vegetation stress was calculated when conditioning on background wetness (SPI-3), with specific cumulative precipitation and heavy rain observations. Figure 10 shows these probabilities in three regions. The cumulative precipitation corresponds to SPI-3, heavy rain intensity corresponds to mR95pT, and the probability is the conditional probability $P(VS = 1 | SPI-3 = x_w, mR95pT = x_h)$. Heavy rainfall intensity (x_h) represents the maximum mR95pT within the 48 days (three 16-day periods) preceding vegetation stress onset. When mR95pT = 0 was observed, it indicates the probability of no heavy rain under a particular cumulative precipitation. The effect of heavy rain on vegetation condition can be measured as the probability difference between $mR95pT = x_h$ and $mR95pT = 0$ under the same SPI-3 conditions. As a sensitivity check, the analysis was repeated using alternative antecedent windows (16, 32, and 64 days) and confirmed that the main probability patterns are robust for 32–64 days, whereas the 16-day window yields a smaller heavy-rain vs. no-heavy-rain contrast (Appendix A.4, Figure A3). These conditional probabilities represent a stratified, descriptive association at the subregional scale. They do not address soil- or management-specific mechanisms or provide a causal explanation for vegetation responses.

These probability estimates may be influenced by uncertainties in precipitation data for areas with sparse station coverage and by residual errors from NDVI gap-filling and smoothing. However, the QA-based sensitivity analysis indicates robustness to common NDVI quality issues. Under near-normal precipitation conditions ($SPI-3 = 0$; $-0.25 < x_w \leq 0.25$), the probability of vegetation stress (VS) was higher when heavy rainfall was observed than when it was not in all three regions. Here, we report the relative change (%) in VS probability relative to the “no heavy rain” case. The relative increase ranged from +11% to +39% in the Sahel, +0.6% to +24% in Southern Africa, and +0.8% to +38% in Eastern Africa. This relative effect generally decreased as SPI-3 increased. Under very wet conditions ($SPI-3 > 1.75$), the relative changes were small and could be negative, ranging from +0.6 to +1.7% in the Sahel, −0.5 to +4.3% in Southern Africa, and −1.2 to +3.4% in Eastern Africa. In addition, VS probability tended to increase with mR95pT across SPI-3 classes.

Excessive soil moisture from heavy rain reduces the air content of the surface soil and increases soil temperature. Decreased air volume results in poor aeration and suppressed root growth. The rise of soil temperature also increases soil respiration and significantly reduces the oxygen content of the soil air, resulting in suppressed root growth [7,40,41]. At cumulative precipitation levels around $SPI-3 = 0$, heavy rain events cause a temporary ex-

cess of soil moisture. Under wet conditions, soil moisture content remains high, regardless of heavy rainfall. So, the higher the SPI3, the smaller the difference in the probability of vegetation stress occurrence according to rainfall intensity.

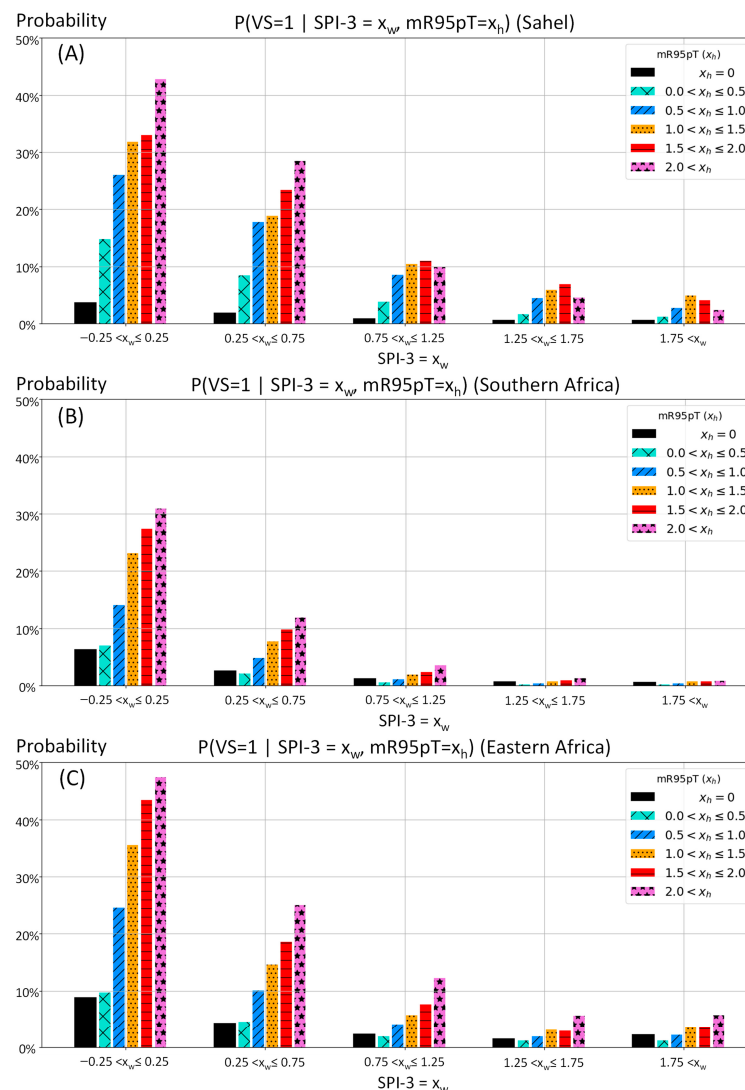


Figure 10. Probability of vegetation stress (VS) when a certain cumulative precipitation (SPI-3) and heavy rain (mR95pT) are observed. Sahel (A), Southern Africa (B), and Eastern Africa (C).

The probabilities exhibited distinct regional differences. In Southern Africa, the difference was nearly zero under high cumulative precipitation, whereas in the Sahel, it increased during heavy rainfall events. These regions also vary in the frequency of tropical cyclones. According to the international disaster database (EM-DAT) [42], the number of disasters classified as “tropical cyclone” was 0 in the Sahel, 26 in Southern Africa, and 7 in Eastern Africa. Regional differences are influenced by multiple factors, such as rainfall regimes and soil and landscape properties that affect infiltration, runoff, and drainage. Since VS is derived from VCI (a relative vegetation condition indicator), it does not exclusively represent waterlogging stress, and mechanistic attribution would require additional soil and hydrological data. Nevertheless, the primary probability patterns remain robust to common NDVI quality issues, as demonstrated by the QA sensitivity analysis (Appendix A.2).

In addition to these regional contrasts, the results highlight the importance of the interaction between climate seasonality and ecosystem functioning, particularly during dry–wet transition dynamics, when interpreting vegetation responses to rainfall extremes

in semi-arid regions. The proposed mR95pT metric is effective for identifying episodic and potentially off-season heavy rainfall anomalies that may be masked by strong seasonal precipitation backgrounds, thereby facilitating more consistent monitoring across diverse climatic regimes. When combined with the stratified probabilistic framework that conditions on background wetness, this approach enables scalable early warning and risk screening for climate-resilient land and agricultural management in data-sparse regions.

4. Conclusions

In this study, we developed a modified heavy rainfall index (mR95pT) to enable robust comparison of extreme rainfall signals across seasons and regions in the Semi-Arid Tropics of Sub-Saharan Africa. The key modification is a day-of-year-dependent heavy rainfall threshold (mER95t) derived from a short moving window, which mitigates the strong seasonal background signal that can dominate constant-threshold approaches. Across the three subregions (Sahel, Southern Africa, and Eastern Africa), the exceedance statistics and event-scale case studies consistently indicated that mR95pT highlights episodic heavy rainfall events more clearly than the original ETCCDI-based index, while reducing spurious concentration around climatological wet-season peaks. Although threshold estimation can be more sensitive around dry–wet transitions when the reference window contains mixed conditions, mR95pT remains well suited to highlighting episodic—and potentially off-season—heavy rainfall signals. This capability is increasingly relevant for monitoring climate-related risk in data-sparse semi-arid regions under intensifying precipitation extremes. Using approximately two decades of CHIRPS precipitation and MODIS NDVI, we further quantified vegetation stress responses to rainfall extremes within a probabilistic framework that combines SPI-3 (background wetness) and VCI-based vegetation stress (VS). This framework allowed us to evaluate changes in vegetation stress likelihood associated with heavy rainfall while controlling the background seasonal wetness. Regionally, Southern Africa showed the lowest vegetation stress probability, whereas Eastern Africa and Sahel exhibited higher probabilities; notably, even around $\text{SPI-3} \approx 0$, vegetation stress probability reached $\geq 35\%$ in Eastern Africa and $>30\%$ in the Sahel when mR95pT exceeded 1.0. Notably, the heavy rainfall signal showed region-dependent behavior, consistent with distinct rainfall regimes across the Sahel and Southern Africa and with the spatially heterogeneous bimodal rainfall pattern of Eastern Africa, underscoring the need for indices that are comparable across diverse climatic settings.

Overall, our approach offers a practical and scalable way to monitor vegetation risks associated with dryness and heavy rain in large, data-sparse regions. It also complements drought-only monitoring common in semi-arid environments. Future work should refine threshold estimation around seasonal changes, test sensitivity to temporal window and drought definitions, and further probe mechanisms using high-resolution rainfall products and in situ observations where available.

Author Contributions: Conceptualization, M.Y. (Megumi Yamashita) and M.Y. (Mitsunori Yoshimura); methodology, K.U. and M.Y. (Mitsunori Yoshimura); formal analysis, K.U.; writing—original draft preparation, M.Y. (Mitsunori Yoshimura); writing—review and editing, M.Y. (Mitsunori Yoshimura) and K.U.; visualization, K.U.; supervision, M.Y. (Megumi Yamashita) and M.Y. (Mitsunori Yoshimura). All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: Author Koki Uda was employed by the company Nippon Koei Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SAT	Semi-Arid Tropics
SSA	Sub-Saharan Africa
CHIRPS	Climate Hazard Group Infrared Precipitation with Stations
CCIs	Climate Change Indices
ETCCDI	Expert Team on Climate Change Detection and Indices
VCI	Vegetation Condition Index
SPI	Standard Precipitation Index

Appendix A

Appendix A.1

The sensitivity of mER95t to the moving-window length was tested by repeating the threshold estimation with $W = 11, 15$, and 21 days, and consistent seasonal patterns were found when summarized at the subregional scale (median across 0.05° pixels for each day of year; Figure A1).

The frequency with which the percentile estimates fall below 10 mm under low wet-day counts was also quantified across N settings and regions, supporting the use of $N = 30$ and the 10 mm minimum threshold for stable estimation (Table A1).

Table A1. Summary statistics of the fraction of pixels for which the wet-day count within the reference window is below a threshold (N) and the wet-day 95th-percentile precipitation is <10 mm, computed for each subregion across days of year. Mean and 95th percentile (P95) values summarize typical and peak-season behavior, and DOY of Max indicates the timing of the annual maximum.

Subregion	N	Mean (%)	P95 (%)	DOY of Max
Sahel	15	43.2	91.4	319
	20	46.0	93.1	319
	25	48.0	94.7	319
	30	49.6	95.4	319
	35	50.6	95.7	319
	40	51.1	95.7	319
	45	51.2	95.5	319
Southern Africa	15	32.1	91.6	166
	20	33.0	92.6	166
	25	33.0	90.9	166
	30	32.6	87.8	269
	35	32.0	85.5	269
	40	31.2	83.8	268
	45	30.3	81.7	268
Eastern Africa	15	49.5	82.1	169
	20	48.8	76.9	169
	25	46.0	73.0	169
	30	42.5	71.8	169
	35	39.3	69.1	169
	40	36.6	66.8	169
	45	34.4	65.0	169

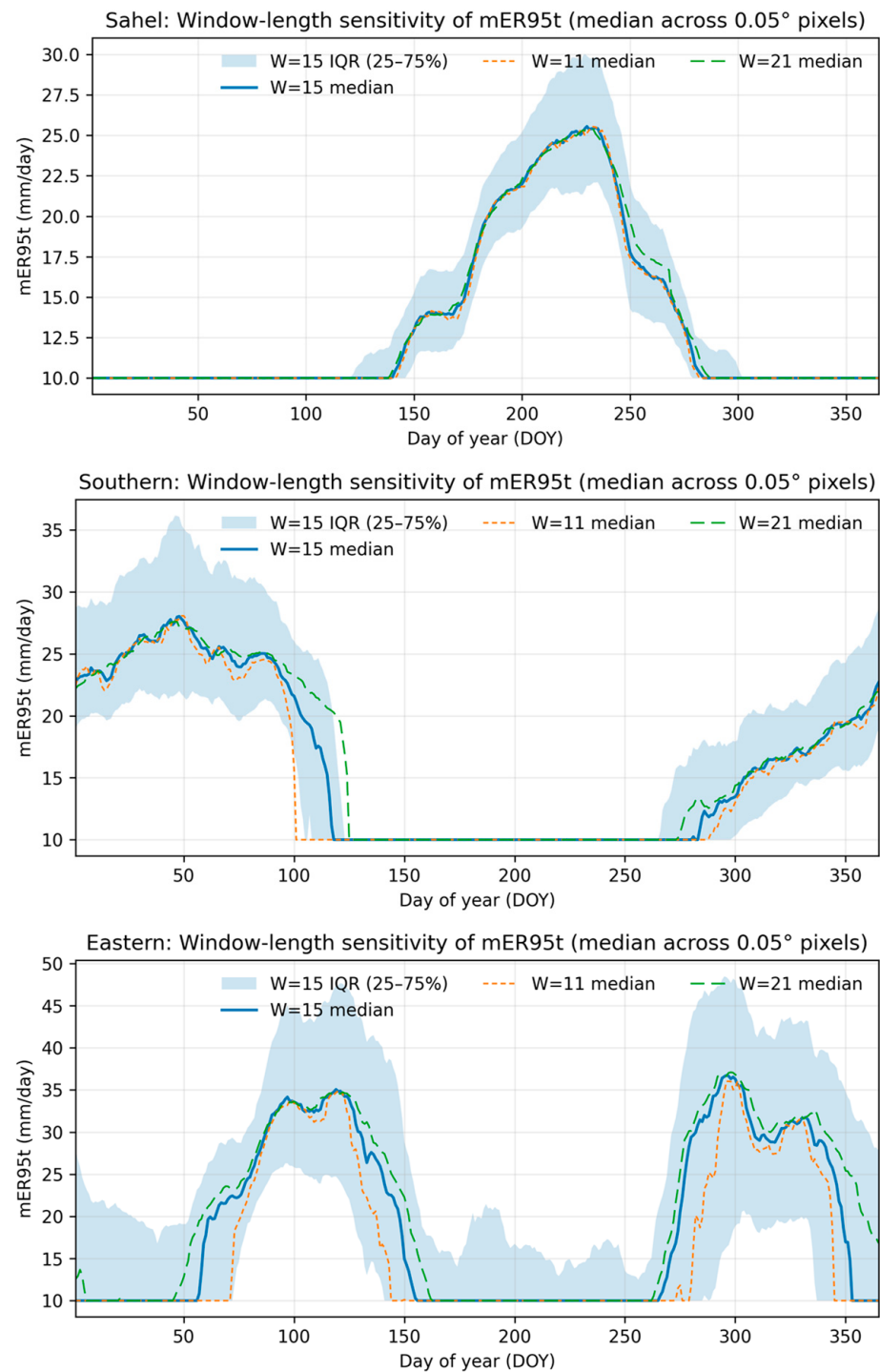


Figure A1. Sensitivity of the day-of-year-dependent threshold (mER95t) to window length ($W = 11, 15, 21$ days). For each subregion, pixel-wise mER95t values (0.05°) were summarized by the median (shading: interquartile range of $W = 15$) for each day of year.

Appendix A.2

To assess the robustness of the VCI-based VS detection against cloud-contaminated observations, we conducted a sensitivity analysis using MOD13C1 quality flags (Figure A2), confirming that 16-day VS pixel counts are consistent across QA screening choices.

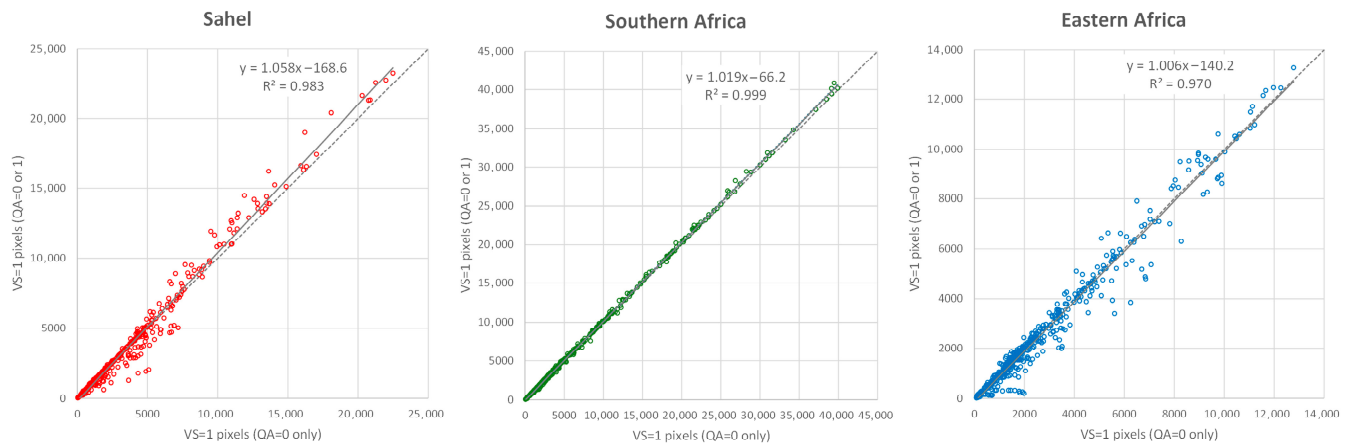


Figure A2. QA flag sensitivity analysis for VCI-based vegetation stress (VS) detection. Scatter plots compare the number of pixels classified as VS (=1) using MOD13C1 observations screened by QA = 0 only (x-axis) versus QA = 0 or 1 (y-axis), aggregated for each 16-day period of year over 20 years (23 periods × 20 years = 460 points) in each subregion. The dashed line indicates the 1:1 relationship ($y = x$). The fitted linear regression (solid line; equation and R^2 shown) demonstrates that VS-area estimates are highly consistent across QA settings.

Appendix A.3

As a robustness check, Spearman's rank correlation indicates that the residual association between SPI-3 and mR95pT is substantially reduced after stratification (Table A2).

Table A2. Spearman's rank correlation between SPI-3 and mR95pT before and after stratification by SPI-3 class.

Subregion	SPI-3 Class	N	Spearman's ρ	p -Value
Sahel	Unstratified	16,410,338	0.241	<0.001
	$-0.25 < \text{SPI-3} \leq 0.25$	3,229,362	0.035	<0.001
	$0.25 < \text{SPI-3} \leq 0.75$	3,121,654	0.04	<0.001
	$0.75 < \text{SPI-3} \leq 1.25$	2,216,976	0.055	<0.001
	$1.25 < \text{SPI-3} \leq 1.75$	1,166,845	0.051	<0.001
	$1.75 < \text{SPI-3} \leq \text{inf}$	631,585	−0.036	<0.001
Southern Africa	Unstratified	25,500,524	0.23	<0.001
	$-0.25 < \text{SPI-3} \leq 0.25$	4,946,028	0.03	<0.001
	$0.25 < \text{SPI-3} \leq 0.75$	4,562,180	0.04	<0.001
	$0.75 < \text{SPI-3} \leq 1.25$	3,481,252	0.05	<0.001
	$1.25 < \text{SPI-3} \leq 1.75$	1,908,130	0.05	<0.001
	$1.75 < \text{SPI-3} \leq \text{inf}$	922,365	−0.020	<0.001
Eastern Africa	Unstratified	11,721,085	0.18	<0.001
	$-0.25 < \text{SPI-3} \leq 0.25$	2,334,112	0.03	<0.001
	$0.25 < \text{SPI-3} \leq 0.75$	2,203,401	0.03	<0.001
	$0.75 < \text{SPI-3} \leq 1.25$	1,501,647	0.04	<0.001
	$1.25 < \text{SPI-3} \leq 1.75$	904,738	0.04	<0.001
	$1.75 < \text{SPI-3} \leq \text{inf}$	750,639	−0.140	<0.001

SPI-3 classes follow Table 1. p -values are <0.001 in all cases due to the large sample size; therefore, effect size (ρ) is emphasized.

Appendix A.4

A sensitivity analysis was conducted using alternative antecedent windows (16, 32, and 64 days) (Figure A3). It confirmed that 32–64-day probability main patterns are robust, whereas the 16-day window yields a smaller heavy-rain vs. no-heavy-rain contrast.

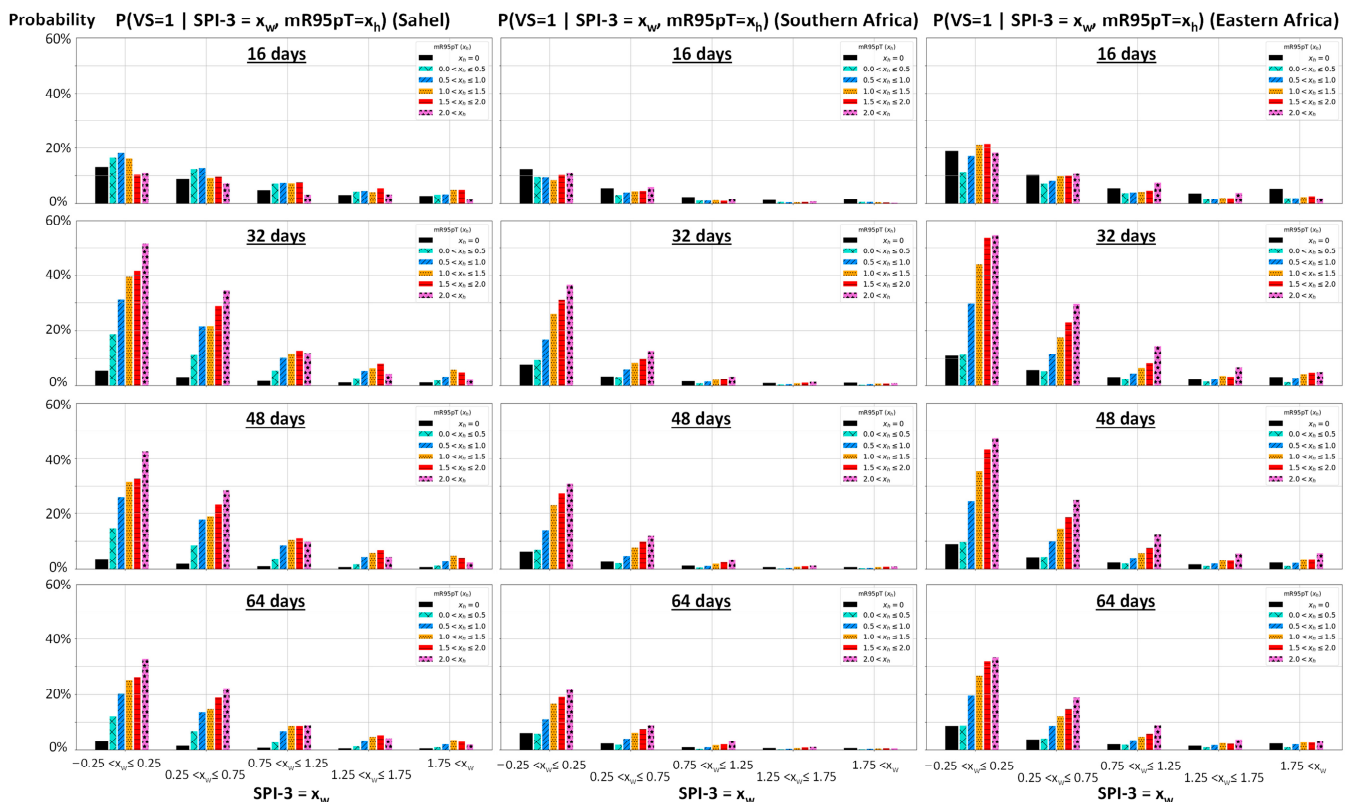


Figure A3. Sensitivity of the antecedent window length used to define heavy rainfall exposure (16, 32, 48, and 64 days).

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