



Full Length Research Paper

Characteristics of Extreme Precipitation and Their Effect on Bean Yield in Rwanda

Marie Adolatha Umutoni^{1,2}, Paul Tilwebwa Shelleph Limbu^{2†}

¹Rwanda Meteorology Agency, P.O. Box 898, Kigali, Rwanda

²Physics Department, University of Dar es Salaam, P.O. Box 35063, Dar es Salaam, Tanzania.

[†]Corresponding author: paul.limbu@gmail.com; ORCID: <https://orcid.org/0000-0001-6467-6403>

ABSTRACT

This study examines the characteristics of extreme precipitation and its effect on bean yield in Rwanda from 1981 to 2017. Over the study area, two rainy seasons, March to May (MAM) and September to December (SOND), account for approximately 80% of total rainfall. The spatial distribution of rainfall over Rwanda revealed that the first three EOF modes of MAM rainfall vary by 72.72 percent over the study period, while the first three EOF modes of SOND rainfall vary by 57.48 percent. The spatial analysis of extreme precipitation reveals that during wet years, the majority of the country's western regions receive significantly more precipitation than the rest. Throughout the study period, the analysis revealed an increasing trend in all extreme precipitation indices. After 2009, a significant increase in the number of wet days (R1mm) and consecutive dry days (CDD) was observed, as was an increase in the number of consecutive wet days (CWD) after 2005. From 1981 to 1989, bean yield increased; however, after 1990, the trend became stationary and began to decline after 2012. Except for R1mm, CDD, and CWD, which showed a negative correlation, the correlation analysis revealed a positive relationship between extreme precipitation indices and bean yield. Despite the fact that there is a weak negative correlation between bean yield and CDD, CDD can be used as a predictor of bean yield due to the significant Granger causality test at the 95% confidence level. Farmers are advised to use alternative methods to increase soil moisture and water holding capacity during the CDD period to avoid yield loss.

ARTICLE INFO

Submitted: May 11, 2022

Revised: September 3, 2022

Accepted: November 14, 2022

Published: December 30, 2022

Keywords: *Extreme precipitation, extreme precipitation indices, EOF, bean yield.*

INTRODUCTION

Rwanda is a landlocked country covering 26,383 square kilometers and dubbed the land of a thousand hills. It is geographically located near the Equator in East Africa, at latitudes of 1°04' and 2°51' south and longitudes of 28°45' and 31°15' north, south, east, and west, respectively, with Uganda,

Burundi, Tanzania, and the Republic Democratic of Congo as shown in Figure 1. Agriculture accounts for 52% of total area, with 0.60 ha per household; 14.9 percent is taken up by water bodies and wetlands; and the remainder is taken up by forest, grazing areas, and human settlements. Rwanda's

agricultural sector contributes 58% of the country's Gross Domestic Product (GDP), employs 80% of the country's active population who live in rural areas, and

accounts for more than 60% of all exported goods (MINAGRI, 2018; Mikova et al., 2015).

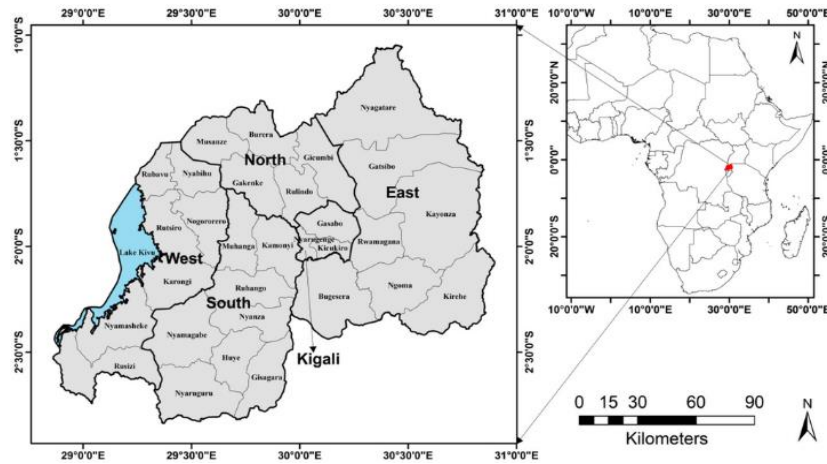


Figure 1: Map of Rwanda (Longitude 28° E-31° E, Latitude 1°04 S-2°51 S), and Map of Africa.

Extreme rainfall is the primary contributor to extreme weather and climate events; it is determined using extreme precipitation indices. Four distinct categories of extreme precipitation indices exist. The first category includes absolute precipitation indices, which indicate the amount of precipitation that fell in a single day and five days (RX1 and RX5). The second category includes indices that exceed the threshold, such as the number of days with heavy precipitation, defined as precipitation exceeding 10 mm (R10mm) per day, the number of days with very heavy precipitation, defined as precipitation exceeding 20mm per day (R20mm), and other user-defined thresholds. The third category of extreme precipitation indices is duration-based and includes the number of consecutive dry days (CDD) and the number of consecutive wet days (CWD). The fourth category contains indices based on percentile thresholds, specifically the 99th percentile of total precipitation (R99pTOT) and the 95th percentile of total precipitation (R95pTOT) (Duan et al., 2015; Zhang et al., 2011). Drought indicators for a particular region are denoted by CDD and CWD, and it is critical to have that knowledge in the agriculture sector. The R95pTOT,

R99pTOT, RX1, and RX5 precipitation indices are used to determine the high-intensity precipitation that results in flash floods and, occasionally, landslides. The R10mm and R20mm indices indicate the frequency of heavy precipitation and very heavy precipitation events, respectively (Karki et al., 2017). Extreme weather events are significant impediments to agricultural production, reducing the quality and quantity of crop production expected. According to IPCC (2007), an increase in temperature of more than 30 degrees Celsius is expected to have a negative effect on crops grown in temperate, tropical, and dry regions. However, the occurrence of extreme weather events may be a major factor in crop failure and failure. Excessive rainfall alters the soil's properties and water-holding capacity or results in soil erosion, which is likely to impair plant growth and production.

Due to their unique nutritional value and affordability, common beans are the primary focus crops in the country, cultivated by a large number of farmers and the most consumed food crop in almost every household. Close to 95 percent of Rwandan households are estimated to be engaged in common bean production, making Rwanda

the country with the highest bean production (Stephen et al., 2017). Beans account for the largest proportion of food crop production on a national scale, accounting for 23% of total land under cultivation (NISR, 2013). The majority of farmers rely on rain-fed agriculture, and rainfall variability can have an effect on farmer production (MINAGRI, 2018).

On the basis of the foregoing, we have developed three critical questions: To begin, how are extreme precipitation events distributed spatially and temporally in Rwanda? Second, how do bean yields vary over time? Finally, to what extent does extreme precipitation have an effect on bean yield? The remainder of the paper is divided into three chapters: Chapter 2 contains the data and methodology, Chapter 3 contains the results and discussion, and Chapter 4 contains the conclusion and recommendation.

MATERIAL AND METHODS

Data collection

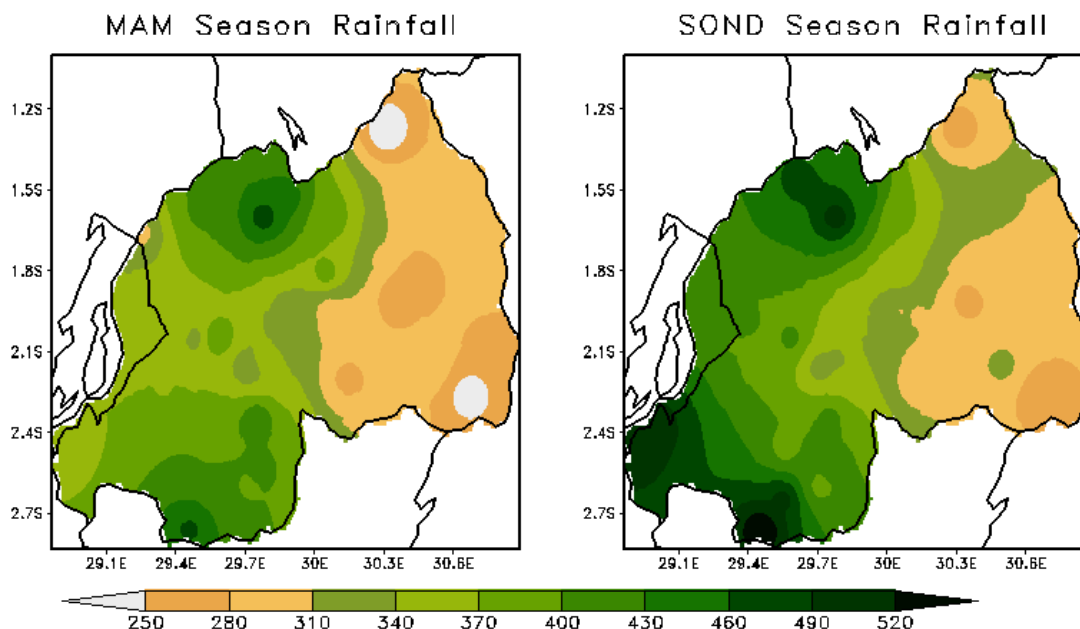


Figure 3: Total rainfall amount during MAM and SON/D rainfall season during the study period.

Data of bean yield

Annual data on bean yields in tons per year

Meteorological station data

Daily rainfall data observed from weather stations, covering the period from 1981 to 2017 are collected from Rwanda Meteorology Agency. They were used to ascertain the severity of the rainfall. The distribution of weather stations used in this study is depicted in Figure 2, while Figure 3 depicts rainfall accumulation during the MAM and SON/D rainy seasons.

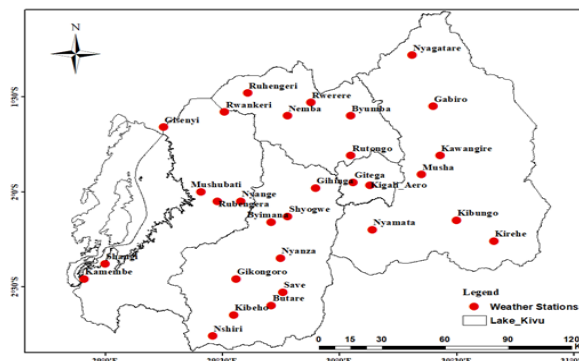


Figure 2: Map of Rwanda representing weather stations used for the study.

were obtained from MINAGRI and the United Nations Food and Agricultural Organization (FAO) for the years 1981 to

2017. The FAO website makes data available for free (FAO, 2019).

Standardized anomaly

By dividing anomalies by the climatological standard deviation, this method converts long-term precipitation to a normal distribution. Numerous studies have used the same method to normalize anomalies and define the criteria for wet and dry years (Lloyd-Hughes and Saunders, 2002).

Empirical Orthogonal Function Method (EOF)

In climate studies, this method is known as Principal Component Analysis (PCA). It is most commonly utilized in climate research to analyze potential spatiotemporal patterns of climate variability. Time-series and eigenvectors are used to break it into time and space functions, respectively. This method was employed in our study to detect the geographical rainfall standardized

anomaly, as well as the time series associated with it.

Extreme precipitation indices computation

Extreme precipitation indices based on the severity and frequency of extreme precipitation in Rwanda from 1981 to 2017 were utilized in this study. Data were analyzed by using the RCLimDex software, which is developed by The Expert Team on Climate Change Detection and Indices (ETCCDI). The software and documentation are available for download at <http://cccma.seos.uvic.ca/ETCCDMI>, which represents an enhancement of ClimDex software used in previous studies (Klein et al., 2009, Caesar et al., 2011). The RCLimDex was used to compute climate indices from daily data. The climate extreme indices were calculated using 12 precipitation indices from RCLimDex, as shown in Table 1.

Table 1: List of ETCCDI precipitation indices used in this research

ID	Indicator name	Description	Unit
Rx1day	Maximum 1-d precipitation	Highest precipitation amount in 1-d period	mm
Rx5day	Maximum 5-d precipitation	Highest precipitation amount in 5-d period	mm
SDII	Simple precipitation intensity index	Mean precipitation amount on a wet day	mm/d
R1mm	Number of wet days	Count of days when daily precipitation ≥ 1 mm	d
R10mm	Heavy precipitation days	Count of days when daily precipitation ≥ 10 mm	d
R20mm	Very heavy precipitation days	Count of days when daily precipitation ≥ 20 mm	d
R50mm	Number of Extremely wet days	Count of days when daily precipitation ≥ 50 mm	d
CDD	Consecutive dry days	Maximum length of dry spell ($RR < 1$ mm)	d
CWD	Consecutive wet days	Maximum length of wet spell ($RR \geq 1$ mm)	d
R95pTOT	Very wet days	Total precipitation due to very wet day	mm
R99pTOT	Extremely wet days	Annual precipitation due to extremely wet days	mm
PRCPTOT	Total precipitation	Annual total precipitation in wet days (>1 mm)	mm

Mann–Kendall Method

The Mann-Kendall (MK) test is a non-parametric statistical test used to analyze trends. MK is typically used to identify whether a group of data values is increasing or decreasing over time, as well as whether the trend is abruptly changing. This method evaluates the trend's significance at a 5% level (Mann, 1945). In this paper, the M–K test was applied to analyze the trend of precipitation extremes indices. In order to

avoid the results of the trend analysis being affected by using different time periods, we used a 30-growth-period moving window which slid every one growth period during the study period. There is a statistically significant change point if they cross and diverge above a specified threshold value.

Correlation analysis

Correlation is a statistical measure of relationship that shows how much two or

more variables change at the same time. It's used to see if two variables have a linear relationship. A positive association exists when two variables increase or decrease in the same direction. The negative relationship, on the other hand, is determined by the opposite direction of two variables; if one rises, the other drops. In this study, the strategy was used to figure out what kind of links exists between extreme rainfall and bean yield. The t-test was also used to test for significance differences in correlation coefficients.

Information flow and causality

The information flow, also known as the information transfer method, was used to quantify the strength of a causal effect relationship by transferring information between entity sources and entity receivers through particular processes in a dynamic system. We will test for causality between extreme precipitation indices and beans yield in this study using the Granger causality test, which was first introduced by (Granger, 1969). This approach is run through a vector auto regression model to see if one variable may predict another (Kurecic and Kokotovic, 2017).

The study arrived at this conclusion based on the following hypothesis:

H_0 = extreme precipitation does not Granger cause bean yield.

H_1 = extreme precipitation Granger causes bean yield.

The null hypothesis of no causal relationship is rejected if the Granger causal relationship becomes significant at 95 percent confidence level.

RESULTS AND DISCUSSIONS

Spatial distribution of rainfall in Rwanda

From January to May, the country's rainfall extends eastward, as seen by the spatial rainfall distribution (Figure 4). Rainfall is concentrated in the southwestern sections of the country in January, and then extends to the northwest in February. The months of March and April are known for having

nearly enough rain to cover the entire country. The convergence of the Congo air boundary (CAB) and the International Tropical Climate Zone (ITCZ) across the region is the reason for this (Nicholson, 2018). Because of the northward shift of the ITCZ outside the study zone, May has seen less rainfall across the country, with the western sections receiving the most. June to August (JJA) had a decrease in rainfall across the country. Because the ITCZ and CAB are beyond the region, with the ITCZ in the far north and the CAB in the far west of Rwanda, this is the case. From September to December, the ITCZ's southern shift caused rains to fall across the country's northwestern region, extending across the entire country.

Furthermore, climatological mean rainfall during the MAM season is characterized by a significant amount of rainfall across the country, with a considerable quantity of rainfall in the western parts (>180mm), as shown in Fig. 5. In comparison to MAM, the country receives less rainfall during the SON season in the western parts. During SON (<90mm), the eastern areas of the country receive less rainfall than during MAM. This demonstrates that rainfall was more evenly distributed across the country during the MAM season than it was during the SON season.

Seasonal and annual variation of rainfall in Rwanda

The temporal distribution in Rwanda was studied using observation monthly rainfall information during a 37-year period from 1981 to 2017. The annual cycle over Rwanda has been discovered to portray the two rainy seasons (MAM and SON) separated by two dry seasons (JJA and JF) fairly effectively (Figure 5a). In MAM, the month of April produces the most rainfall between these two rainy seasons, comparable to what has been discovered by other researchers (Ngarukiyimana et al., 2018; Mikova et al., 2015; Muhire, 2015).

The result is consistent with the monthly rainfall spatial distribution (Figure 5c, d), which shows an increase in rainfall from March to May and September to December.

It also demonstrates that the two rainy seasons (MAM and SON) account for over 80% of the total rainfall received across the research area (Figure 5b).

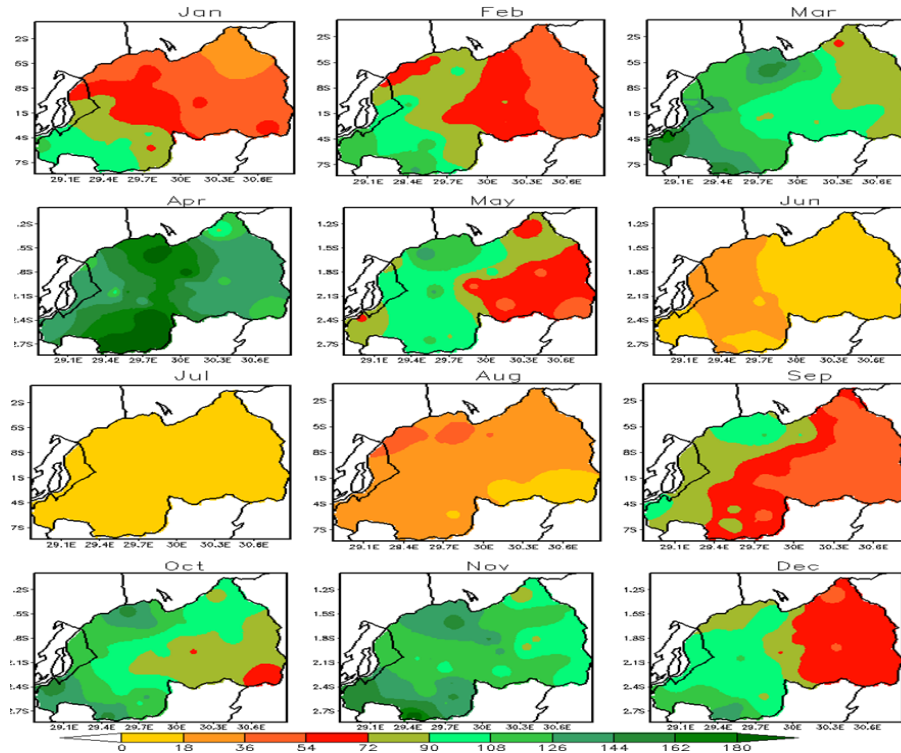


Figure 4: The spatial distribution of monthly rainfall climatology (mm/month from 1980-2017 over Rwanda) based on observation station data.

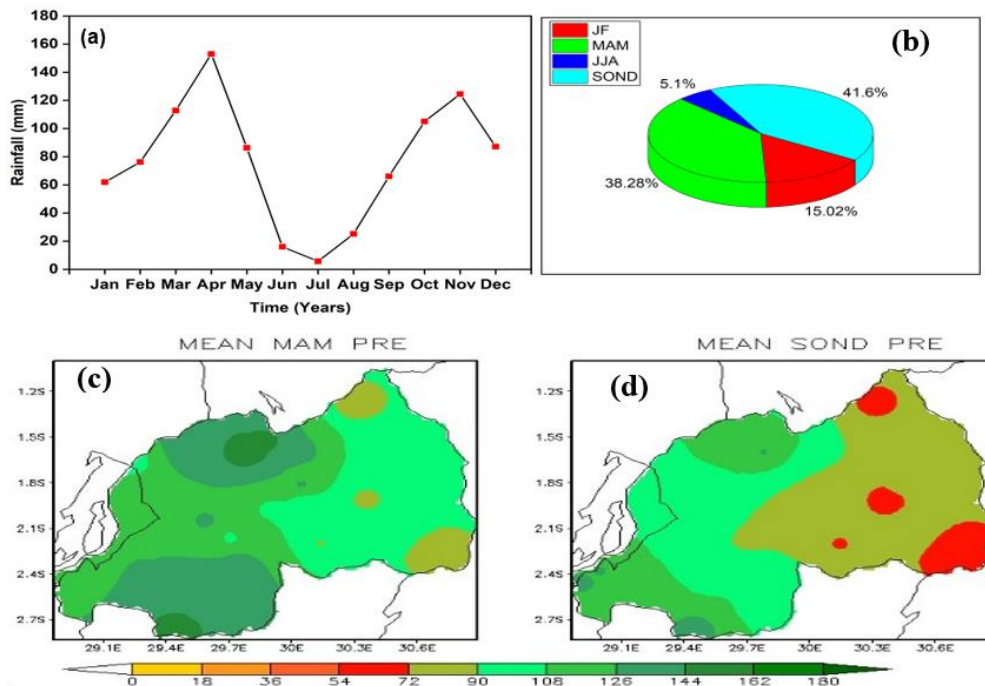


Figure 5: (a) The annual rainfall cycle (mm) during the period 1981-2017, (b) The contribution of seasonal rainfall in percentage over Rwanda for the same period; Spatial distribution of rainfall season over Rwanda during (c) MAM and (d) SON.

Spatiotemporal variation of rainfall in Rwanda

The EOF was utilized to better comprehend the spatial distribution of rainfall during the MAM and SOND seasonal rains, which correspond to the agricultural calendar

across the country, by displaying its predominant modes. The top three EOF modes account for 72.72 percent of total variation in MAM and 57.48 percent in SOND, respectively, See Table 2.

Table 2: Percentages of the total variances explained by EOF modes from 1 to 3 and corresponding % of accumulative variance for MAM and SOND rainfall seasons

EOF Modes	MAM		SOND	
	Variance (%)	Cumulative Variance (CV) %	Variance (%)	CV (%)
EOF 1	40.26	40.26	40.16	40.16
EOF 2	25.71	65.95	9.82	49.98
EOF 3	6.75	72.72	7.40	57.48

Empirical Orthogonal Function for MAM rainfall season

In Figure 6a, the eigenvector of the first dominant mode of EOF (EOF 1) explains 40.26 percent of the overall variation in rainfall across the country. During MAM, the country exhibits West – East patterns, with positive loadings to the western portions and strong positive loadings over the northern and southern sectors, and negative loadings to the eastern parts and strong negative loadings over the northern and southern sectors. Furthermore, the pattern exhibits significant rainfall variability in both the north and south. The matching time series of EOF 1 (PC 1) is shown in Figure 6c, with an inter-annual and inter-decadal temporal scale. The wet and dry years with a standardized anomaly of more (less) than 1 were determined using the standardized anomaly index. PC 1 experienced six (6) wet years, including 1981, 1986, 1988, 1995, 2012, and 2013, and five (5) dry years, including 1984, 1999, 2000, 2014, and 2017, with 2017 and 2013 being the extreme dry and wet years, respectively. The second mode of EOF (EOF 2) is responsible for 25% of the total variation (Figure 6b). It depicts a unimodal

pattern with substantial positive loading in the center and eastern regions. The weakest positive loading seen across the northern and southern regions explains why rainfall in these areas is less variable. Figure 6d depicts the EOF 2-time series (PC2). The inter-decadal time scale is prominent, with six (6) wet years (1982, 1985, 1986, 1989, 1991, and 1912) and three (3) dry years (2013, 2014, and 2016).

Empirical Orthogonal Function for SOND rainfall season

For the SOND rainy season, the first mode of EOF (EOF1) yields a variance of 40.16 percent of total rainfall variability over Rwanda. This mode has a unimodal pattern that is linked to positive loading throughout the country. The strong positive loading seen over the western parts of the study area indicates that there was more rainfall in that area during the study period. Even though the northeastern parts of the country receive less rain, rainfall in that area is highly variable. Figure 7c depicts inter-annual and inter-decadal on a temporal scale, with four (4) wet years (1982, 1994, 2011, and 2014) and four (4) dry years (1991, 1993, 2005,

and 2017). Figure 7b explains 9.82 percent of the overall variance of the SOND rainfall season's second EOF (EOF2). It shows the positive and negative loading dipole patterns over the study area. It has negative loadings in the west and east and positive loadings in the south. The inter-decadal time scale is represented by the major component of EOF 2 (PC 2) in Figure 7d, with three (3) wet years (2001, 2011, 2013) and five (5) dry years (1983, 1988, 1989, 2012, and 2016).

Temporal variation of extreme precipitation events

Figure 8 depicts the annual variations of extreme rainfall frequencies over Rwanda from 1981 to 2017, during a 37-year period. Seven positive years, including 1997, 1998, 2001, 2002, 2005, 2006, and 2011, and six negative years, including 1983, 1984, 1992, 1993, 2016, and 2017, were detected using the standardized anomaly of annual wet days (R1mm) greater (less) than 1(-1).

(Figure 8a). Years having a high (low) number of wet days are considered favorable (negative). From 1997 to 2011, the country saw an increase (down) in the number of wet days (1983 to 1993).

Figure 8b demonstrates that the years 1990, 1995, and 2002 had the highest number of continuous dry days, while 2007, and 2011 had the lowest number. The years 1988 and 1995 set records for the most days with heavy precipitation of at least 10 millimeters per day (Figure 8c). The largest number of days with very heavy rainfall over 20mm per day was reported in the years 1987, 1988, and 1994. In the years 2002 and 2017, there were less days recorded (Figure 8d). Figure 8e depicts the highest number of consecutive wet days in 1997 and 2006, as well as the lowest number in 1991, 1993, and 2017. The most days with very heavy precipitation over 50mm per day were reported in the years 1988, 1994, and 1995. The years 2001, 2002, and 2017 had fewer days than the previous three (Figure 8f).

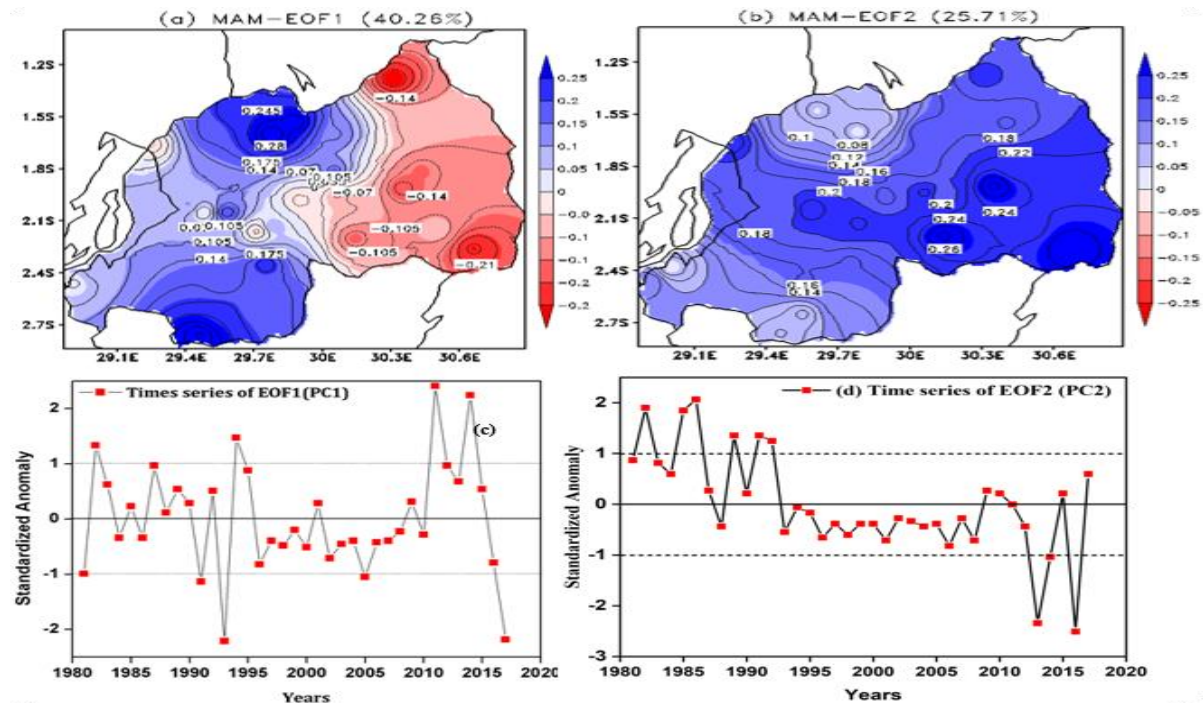


Figure 6: The spatial map of MAM rainfall for (a) First dominant mode (EOF1), (b) Second dominant mode (EOF2) and its corresponding principal component time series in (c) and (d), respectively.

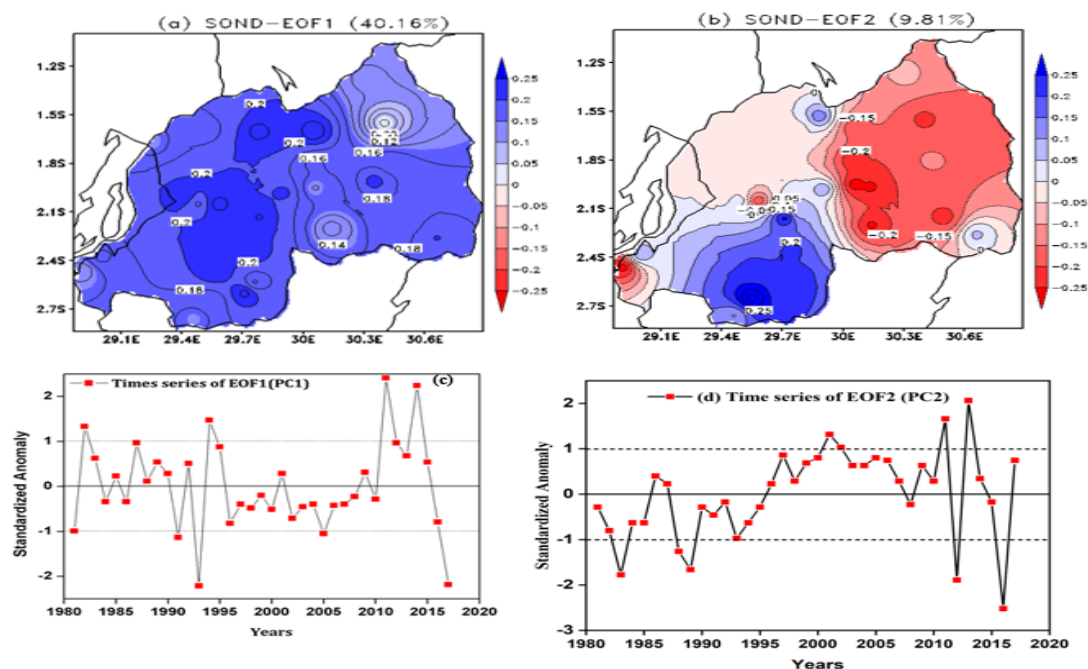


Figure 7: The spatial map of SOND rainfall for (a) First dominant mode (EOF1), (b) Second dominant mode (EOF2) and its corresponding principal component time series in (c) and (d), respectively.

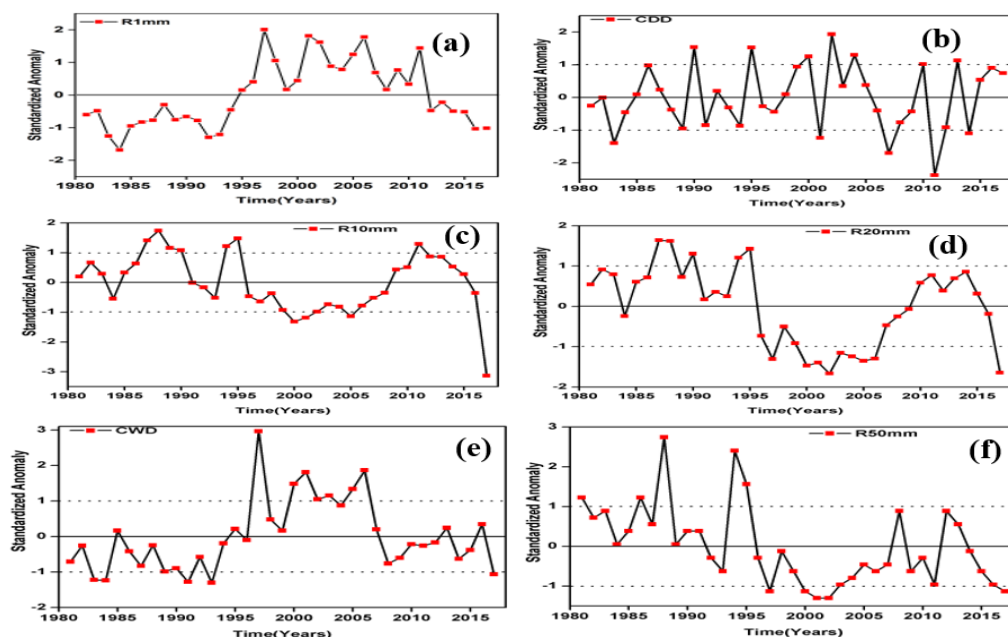


Figure 8: The annual variation of extreme rainfall frequencies (a) number of wet years (R1mm), (b) Consecutive Dry Days (CDD), (c) number of heavy precipitation days (R10mm), (d) number of very heavy precipitation days R20mm, (e) number of consecutive wet days (CWD), (f) number of extremely wet days R50mm.

Figure 8b demonstrates that the years 1990, 1995, and 2002 had the highest number of continuous dry days, while 2007, and 2011 had the lowest number. The years 1988 and 1995 set records for the most days with

heavy precipitation of at least 10 millimeters per day (Figure 8c). The largest number of days with very heavy rainfall over 20mm per day was reported in the years 1987, 1988, and 1994. In the years 2002 and 2017,

there were less days recorded (Figure 8d). Figure 8e depicts the highest number of consecutive wet days in 1997 and 2006, as well as the lowest number in 1991, 1993, and 2017. The most days with very heavy precipitation over 50mm per day were reported in the years 1988, 1994, and 1995. The years 2001, 2002, and 2017 had fewer days than the previous three (Figure 8f).

Temporal variation of extreme precipitation amount

Figure 9 depicts the annual variations of extreme rainfall quantity over Rwanda over a 37-year period from 1981 to 2017. The number of rainy and dry years was calculated using a standardized anomaly of 1. Figure 9a shows that the wet years in terms of yearly total precipitation in the country were 1987, 1988, 1994, and 1995, whereas the dry years were 1984, 2000, 2011, and 2017. In 1987 and 1988, more than 95 percent of the total annual precipitation across the country was recorded (Figure 9b). The years 1988 and 1994 were classified as rainy years by 99 percent of the yearly total precipitation, while 2001 and 2002 were classified as dry years (Figure 9c). The years 1987, 1988, and 1994 had the most precipitation in a single day, while 2002 and 2005 had the least amount of precipitation per day (Figure 9d). Figure 9e shows the maximum precipitation on five days in 1983 and 1985, and the minimum precipitation in 1997 and 2017. Figure 9f depicts the average precipitation on wet days throughout a given year, implying that a specific quantity of precipitation was recorded on each rainy day. It indicates that in 1987 and 1988, every wet day had a high amount of precipitation, however in 2002 and 2017, every wet day had a lower amount of precipitation.

Spatial variation of extreme precipitation

When compared to the eastern sections, the western parts receive a lot of total precipitation during wet years (Figure 10a). In dry years, the eastern regions of the

country receive less precipitation than the western parts, yet the western parts appear to receive enough rainfall ($>800\text{mm}$) (Figure 10b). As a result, the eastern regions of the country are more susceptible to drought than the western parts. The southern regions were found to have a high quantity of yearly total precipitation at 95 percentiles during the rainy years (Figure 10c). Most places receive less precipitation during the dry years (Figure 10d). Figure 10e illustrates that several portions of the southwestern, central, and northwestern regions of the country received a lot of rain due to particularly wet days when the percentile was extended to 99 percent of total precipitation. However, majority of the country, particularly in the central region, is exceedingly arid (Figure 10f).

Furthermore, during wet years, the western and central sections of the country received the most precipitation in a single day than the rest of the country (Figure 11a). During dry years, most portions of the country got less total precipitation in a single day, with the exception of a few tiny areas in the south and east (Figure 11b). During wet years, the maximum precipitation amount recorded in consecutive five days is more likely to be reported in the south than in the rest of the country. During wet years, the northeastern region received less precipitation than the rest of the country ($\geq 80\text{mm}$ in five days) (Fig 11c). Except for the southern sections of the country, much of the country experiences less precipitation during dry years (Figure 11d). The simple precipitation intensity index (SDII) was used to determine which regions were more likely to be wet or dry during wet or dry years. In wet years, Figure 11e illustrates that the majority of the country, particularly the southern regions, appears to be wet. This indicates that, in comparison to other sections of the country, these regions receive a lot of rain on rainy days. Figure 11f indicates that the eastern and southern sections of the country receive a lot of precipitation during dry years, indicating that same areas still get the most rain when

it rains.

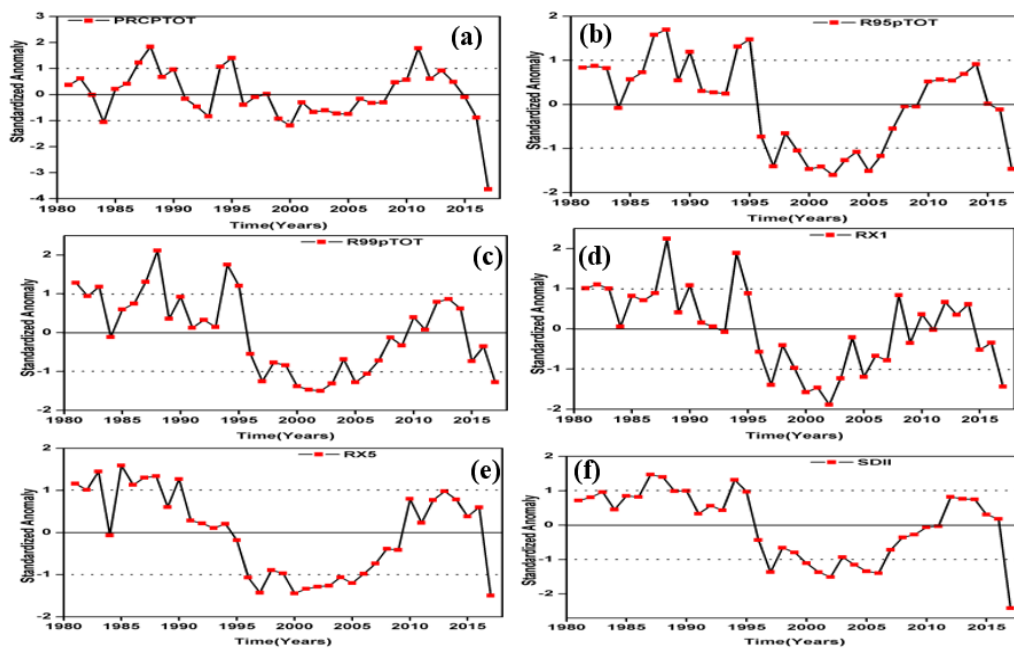


Figure 9: the annual variation of extreme rainfall amount (a) Annual total precipitation (PRCPTOT), (b) Precipitation due to very wet days (R95pTOT), (c) Precipitation due to very extremely wet days, (R99pTOT), (d) Maximum Precipitation one day RX1, (e) Maximum Precipitation in five days RX5, (f) Single Precipitation Intensity Index (SDII).

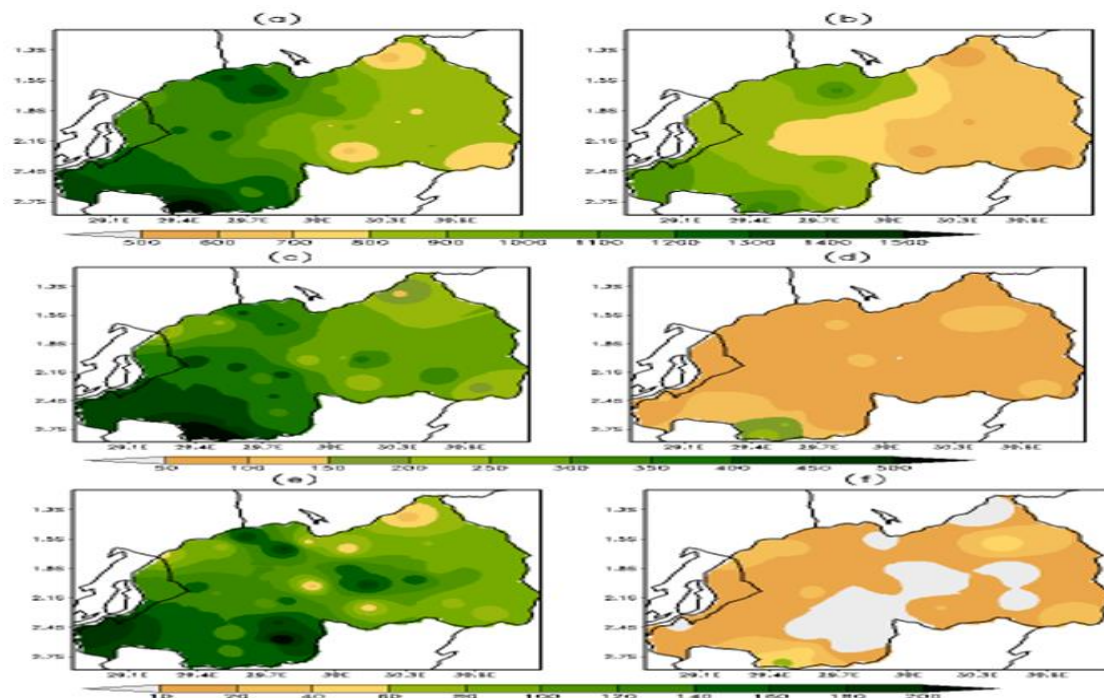


Figure 10: Spatial distribution of Annual Total Precipitation (PRCPTOT) during (a) wet, (b) dry years; Precipitation due to very wet days (R95pTOT) during (c) wet (d) dry years; Precipitation due to very extremely wet days (R99pTOT) during (e) wet, (f) dry years.

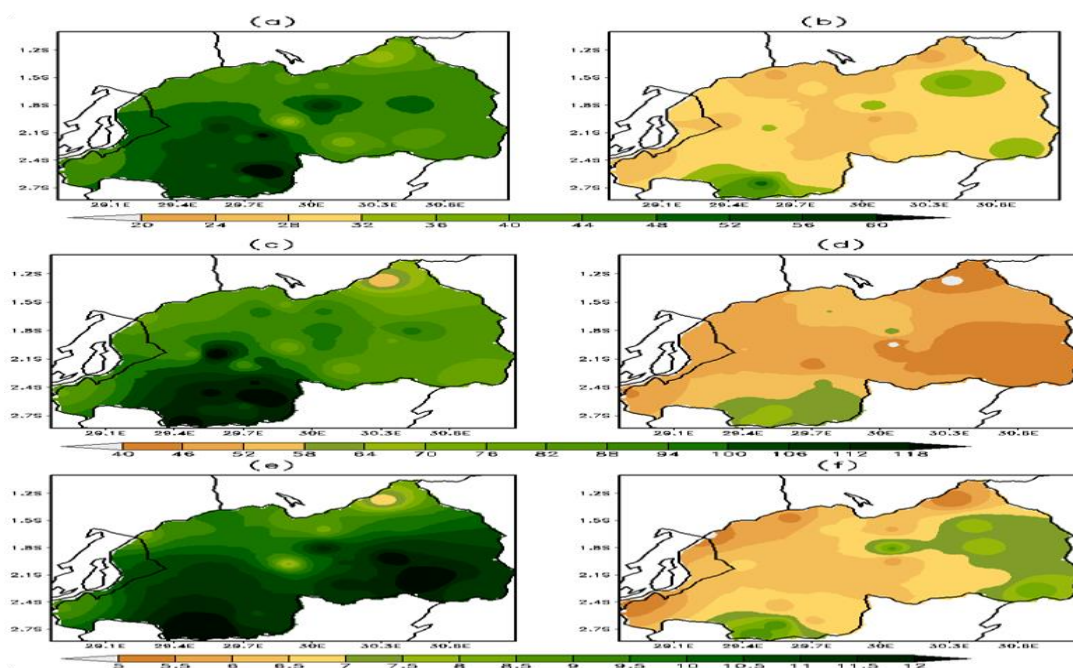


Figure 11: Spatial distribution of Maximum precipitation in one day (RX1) during (a) wet, (b) dry years; Maximum precipitation in five days (RX5) during (c) wet (d) dry years; Single precipitation intensity index (SDII) during (e) wet, (f) dry years.

Trends and Abrupt Change of extreme rainfall

Using Mann–Kendall, the data are displayed as a temporal scale that shows the rainfall extremes variability (MK). The MK test was used to determine whether the country's severe occurrences are rising or decreasing from year to year, and if so, whether this trend is significant or not at the 95 percent confidence level. It also aids in determining whether the rising trend is caused by climate change.

Temporal characteristics of extreme precipitation frequency

For the whole study period, Figure 12a depicts an increasing trend in the number of wet days (R1mm). After 2009, the trend becomes statistically significant at the 95 percent confidence level, most likely as a result of the rapid change in R1mm that occurred about 2007. During the study period, Figure 12b of consecutive dry days (CDD) likewise indicates an increasing tendency. Between 2001 and 2008, there was an abrupt change in CDD, which coincided with a large rise in CDD in the country following 2009. From 1981 to 1989, the number of highly precipitation days (R10mm) increased although not significantly. The trend became largely stalled after the sharp change witnessed from 1989 to 1992, as shown in Figure 12c. Consecutive wet days (CWD)

results reveal an upward trend throughout the research period. Because of the rapid change in CWD after 2005, the growing trend becomes statistically significant at a 95% confidence level (Figure 12d). In Figure 12e, the analysis of the number of very heavy precipitation days (R20mm) reveals an increasing trend that was not significant from 1981 to 1989. After the rapid change in R20mm that happened between 1989 and 1992, the trend remains stationary. Figure 12f of exceptionally heavy precipitation days (R50mm) shows an increasing trend from 1981 to 1991, then an abrupt turnaround from 1991 to 2002, then an increasing trend from 2002 to 2006, and finally a stationary trend.

Temporal characteristics of extreme precipitation amount

Figure 13a shows the increasing trend in annual total precipitation (RCPTOT), which was not significant from 1981 to 1989. Following the dramatic change in PRCPTOT that occurred between 1981 and 1992, the trend becomes stationary noteworthy after 1989. Figure 13b showing the 95th percentile of yearly total precipitation (R95p TOT) shows a non-significant increasing trend from 1981 to 1992. Following the dramatic change in R95pTOT that occurred between 1989 and 1992, the trend becomes stationary noteworthy after 1992. A non-significant increasing trend was seen from 1981 to

1991, as shown in Figure 13c of 99 percent of annual total precipitation (R99pTOT). After the dramatic change in R99pTOT from 1991 to 1996, the trend becomes stationary significant at the 95 percent confidence level. Figure 13d,f shows a stationary trend for maximum precipitation in a

single day (RX1) and single precipitation intensity index (SDII) after 1994. From 1981 to 1989, both data show a non-significant upward trend. During the research period, Figure 13e of maximum precipitation in five days (RX5) reveals a non-significant stationary pattern.

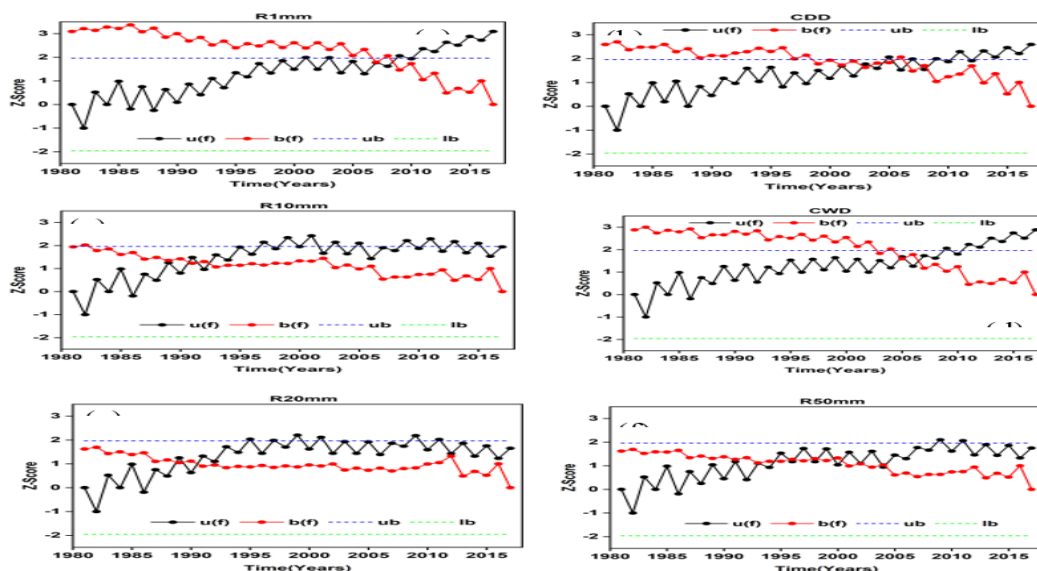


Figure 12: Trend analysis of extreme precipitation days (a) number of wet days (R1mm), (b) Consecutive Dry Days (CDD), (c) number of heavy precipitation days (R10mm), (d) number of very heavy precipitation days R20mm, (e) number of consecutive wet days (CWD), (f) number of extremely wet days R50mm. As derived from the sequential Mann–Kendal test u(f) is the forward sequential statistic while b(f) is the backward sequential statistic. The upper boundary is denoted by ub while lb is the lower boundary.

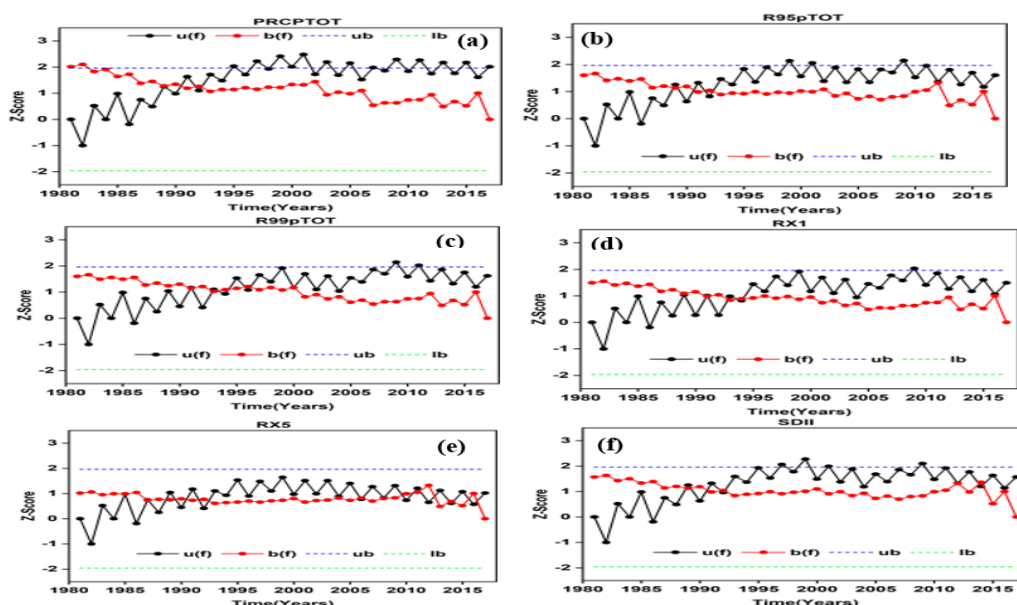


Figure 13: Same as Figure 12., except Trend analysis of extreme precipitation (a) Annual total precipitation (PRCPTOT), (b) Precipitation due to very wet days (R95pTOT), (c) Precipitation due to very extremely wet days, (R99pTOT), (d) Maximum Precipitation one day RX1, (e) Maximum Precipitation in five days RX5, (f) Single Precipitation Intensity Index (SDII).

Bean yield characteristics

Land preparation, seeding, growth, and harvesting of beans are divided into two seasons, A and B, which correspond to the rainfall seasons SOND and MAM, respectively. Season A begins with seeding activities in September and continues through October, with growing seasons in November and December, and season A

concludes with harvesting activities in January. Because of the high rainfall in MAM, sowing begins in March, followed by the growing season in April and May, and the harvesting season in June. Beans are grown in all sections of the country and take three to four months to mature from sowing to maturity.

Table 3: Agricultural calendar concerning bean crops

Period	J	F	M	A	M	J	J	A	S	O	N	D
Season A												
Season B												

Sowing period
 Growing period
 Harvesting period

During the study period, the average yield productivity was 0.783 tonnes/ha/year. In Figure 14a, the outcome of temporal fluctuation in bean yield is divided into three phases: 1981-1990, 1991-2006, and 2007-2017. The yield was high in the beginning. The country received a low yield in the second phase, most likely as a result of extreme climate events such as ENSO in 1997/1999. In comparison to the first phase, the country collected a high output during the third phase. This was due to the Rwandan government's adoption of technology such as improved seeds, fertilizers, and crop intensification production tactics in order to boost and

increase bean yields for the country's food security. Figure 14b demonstrates that high yield occurred 21.62 percent of the time during the study period, low yield occurred 18.9 percent of the time during the study period, and normal yield occurred 59.3 percent of the time during the study period. This indicates that the country produced enough beans throughout the study period. During the study period, the outcome demonstrates a rising trend in bean yield (Figure 14c). Before 1989, the trend was increasing, but with the dramatic change in bean production in 1990, the trend became stationary. Furthermore, the rapid reduction in bean production reported after 2012 was not significant at the 95 percent confidence level.

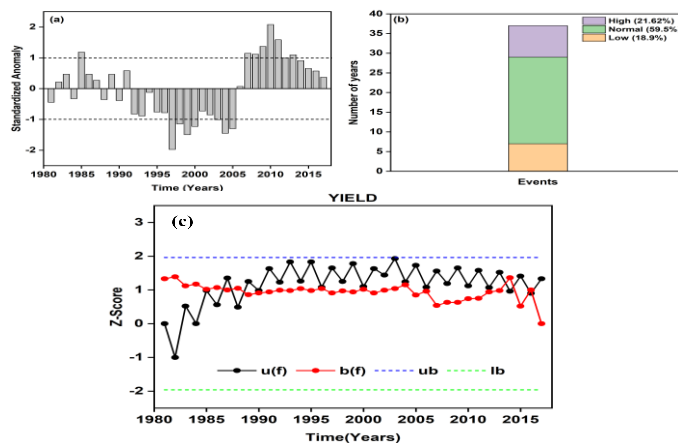


Figure 14: (a) Temporal variation of bean yield (b) occurrence of low, high and normal bean yield, (c) Trend analysis of bean yield over Rwanda during the period 1981-2017.

Relationship extreme precipitation frequency and bean yield

The number of rainy days (R1mm) and bean yield throughout the study period had a weak negative connection ($r= -0.28$), as shown in Figure 15a. At a 95% confidence level, there is a substantial negative correlation between consecutive dry days (CDD) and bean yield ($r= -0.34$). (Figure 15b). It means that if the research area has a string of dry days in a row, the bean production in that year will be poor. Heavy precipitation days (R10mm) had a weak positive connection ($r= 0.39$) with bean yield (Figure 15c). Despite the fact that the link appears to be weak, it is statistically significant at a 95% confidence level. Figure 15d shows a substantial positive connection between very heavy precipitation days (R20mm) and bean yield ($r=0.46$) at a 95% confidence level. This indicates that bean yields will likely increase during this time. At the 99 percent confidence level, the correlation between

consecutive wet days (CWD) and bean yield is considerably negative ($r=-0.48$) (Figure 15e). Although (R20mm) is positively connected with bean yield, consecutive wet days appear to diminish bean output; hence, precipitation events should not occur in a row for higher yield. Bean yield is strongly associated ($r= 0.19$) with really heavy precipitation days (R50mm) (Figure 15f). This favorable link was not statistically significant during the research period.

Relationship between extreme precipitation amount and bean yield

Except for Figure 16a, which indicates a non-significant positive association, all figures show substantial correlation between precipitation and yield. Furthermore, at a 95% confidence level, Figure 16b, e shows a substantial association, implying that bean yield is significantly linked to R95pTOT and RX5.

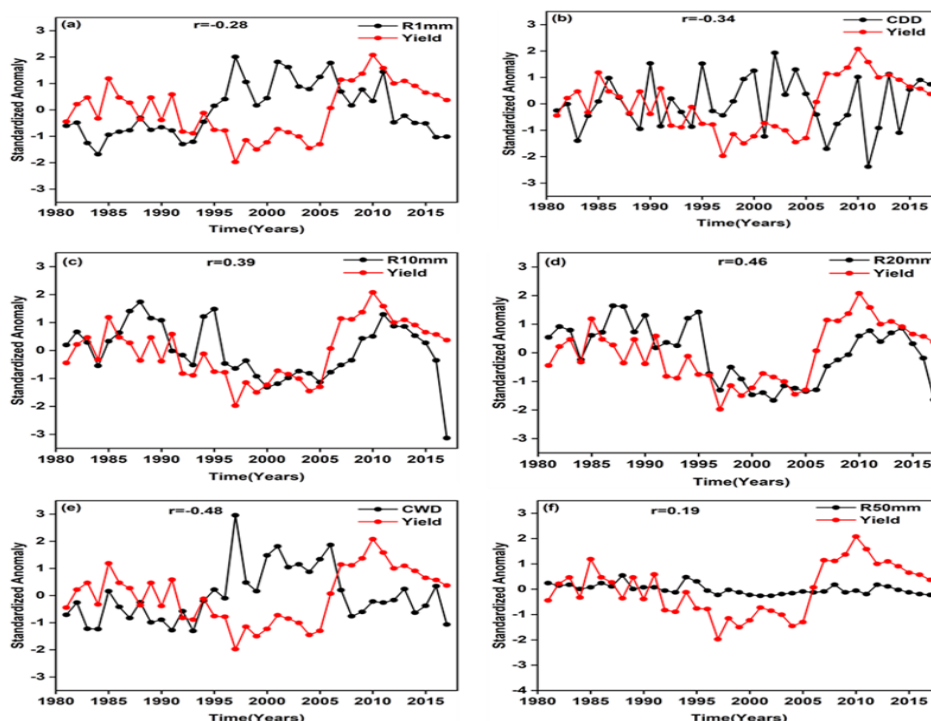


Figure 15: Relationship between extreme precipitation events (a) number of wet days (R1mm), (b) Consecutive Dry Days (CDD), (c) number of heavy precipitation days (R10mm), (d) number of very heavy precipitation days R20mm, (e) number of consecutive wet days (CWD), (f) number of extremely wet days R50mm and bean yield over the study period.

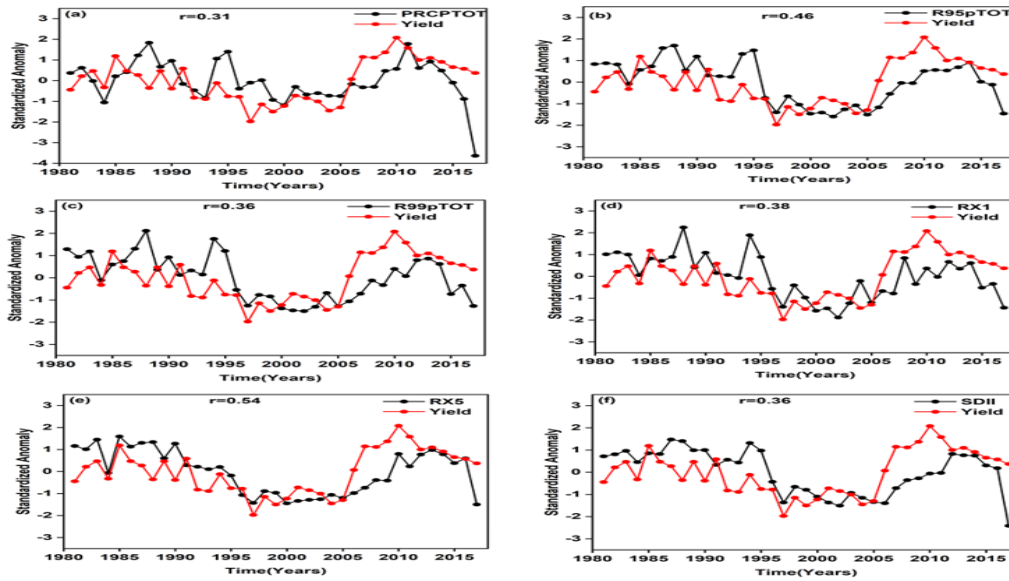


Figure 16: Relationship between extreme precipitation amount (a) Annual total precipitation (PRCPTOT), (b) Precipitation due to very wet days (R95pTOT), (c) Precipitation due to very extremely wet days, (R99pTOT), (d) Maximum Precipitation one day RX1, (e) Maximum Precipitation in five days RX5, (f) Single Precipitation Intensity Index (SDII) and beans yield over the period 1981-2017.

Influence of extreme precipitation on bean yield

Research of the causal association between excessive precipitation and bean yield is required since it provides information to policymakers, stakeholders, and all others concerned. As a result of the impacts of extreme precipitation, they can take the necessary steps. Farmers must be mindful of excessive precipitation in order to increase bean output and food security.

Stationary test

The Vector auto-regression model (VARM) was used to examine if variables are stationary based on the null hypothesis that variables are non-stationary in order to investigate the causal link. Annual extreme precipitation and bean production data from 1981 to 2017 were utilized to develop the empirical technique. To guarantee that all variables in the time series are integrated and to eliminate any potential of auto correlation, the unit root approach was employed to examine individual variables in the time series. In a regression model, non-stationary data might lead to skewed findings. Because non-stationary data

produces erroneous conclusions, it must be detrended before further research. Except for consecutive dry days (CDD), consecutive wet days (CWD), and exceptionally wet days (R50mm) in Table 4, all variables in the model are stationary, and the null hypothesis is accepted when the p-value is less than 0.05 at the confidence level.

Table 4: Test for unit roots in vector auto-regression model

Excluded	F-Statistic	Significance test (p-Value)	Decision
Yields	1.264277	0.2334	Rejected
CDD	43.19973	0.0000	Accepted
CWD	10.08967	0.0298	Accepted
PRCPTOT	3.228008	0.3761	Rejected
R10mm	2.154651	0.5379	Rejected
R20mm	3.419425	0.3517	Rejected
R50mm	13.91166	0.0077	Accepted
R95pTOT	3.638194	0.3253	Rejected
R99pTOT	5.695994	0.1524	Rejected
RX1	8.041005	0.0632	Rejected
RX5	3.923157	0.2878	Rejected
R1mm	4.503232	0.2376	Rejected
SDII	1.664909	0.6234	Rejected

Causality test

The Granger causality test was used to investigate the structure of the causal link between severe precipitation and bean yield. Granger causality is a statistical hypothesis method for testing if a time series of a variable may be used to forecast another variable. Under the null hypothesis that excessive precipitation does not impact bean yield, the evaluated results of the causality test are based on uni-direction. In the Granger causality test, all variables were considered stationary and stable. The significance of the causative association between excessive precipitation and bean yield is demonstrated in Table 5. If the probability value falls below the commonly accepted significance level test, the null hypothesis is rejected (i.e., 0.01, 0.05, and 0.1). When two lagged was applied at the 95 percent confidence level, the results in Table 5 indicated the existence of unidirectional causality extending from CDD to bean yield. CDD can be used to predict bean yields.

Table 5: Granger Causality Tests for extreme precipitation indices and bean yield

Excluded	F-Statistic	p-Value	Decision
CDD	5.09279	0.0125	Reject
CWD	0.019785	0.9804	Accept
PRCPTOT	0.84672	0.4388	Accept
R10mm	0.94143	0.4013	Accept
R20mm	0.70460	0.5023	Accept
R50mm	0.03828	0.9625	Accept
R95pTOT	0.49038	0.6172	Accept
R99pTOT	0.27034	0.7650	Accept
RX1	0.08629	0.9176	Accept
RX5	0.48364	0.6213	Accept
R1mm	0.51433	0.6031	Accept
SDIII	0.49271	0.6158	Accept

CONCLUSION AND RECOMMENDATION

The monthly rainfall over Rwanda is mostly impacted by the migration of the ITCZ, according to the spatial distribution of monthly rainfall. From January to May,

when the ITCZ moved northward, the western parts of the country received more rain. The months of March and April are marked by a nearly adequate amount of rainfall across the country. This is due to the convergence of the Congo air boundary (CAB) and the International Tropical Climate Zone (ITCZ) across the region. From September through December, the ITCZ's southward march brought rain to the country, ranging from the northwest to the rest of the country. This means that the ITCZ movement is mostly responsible for the country's current rainfall regimes (i.e., MAM and SOND).

The spatial distribution of rainfall in Rwanda is disclosed by revealing that 72.72% of the first three EOF modes of MAM rainfall and 57.48% of the first three EOF modes of SOND rainfall vary around the country during the study period. MAM rainy season has more fluctuation than SOND rainy season between the two seasons. Extreme precipitation analysis demonstrates that the western sections of the country receive more precipitation during rainy years than the eastern parts, and the eastern parts receive less of the yearly total precipitation during dry years. As a result, the eastern regions of the country are more prone to drought than the western parts. During rainy years, the southwestern regions obtained a significant proportion of the 95 percentiles of yearly total precipitation, however during dry years, most sections of the regions receive less precipitation. The southwestern, central, and northwestern portions of the country got a significant quantity of precipitation during particularly wet days in wet years. Furthermore, during wet years, the western and central sections of the country accumulated the most precipitation in a single day than the rest of the country. During wet years, the southern sections of the country are more likely to get a large amount of precipitation in a five-day period than the northeastern part of the country. In general, most sections of the country appear to be wet during wet years,

particularly the central and southern parts on wet days. When it rains during dry years, the eastern and southern areas of the country get the most precipitation.

Throughout the study period, the trend for all extreme precipitation indicators was increasing. The trend for each index, with the exception of R1mm, CDD, and CWD, becomes stationary following the dramatic change. In R1mm, CDD, and CWD, a considerable upward trend was seen after 2009. From 1981 through 1989, however, bean yields showed an upward trend. The trend became stationary after 1990, and then began to decline after 2012. Except for R1mm, CDD, and CWD, where there was a negative association, the results of this study revealed a favorable relationship between extreme precipitation indices and bean production. R20mm and RX5 had strong positive correlations of 0.46 and 0.54, respectively, while CWD had the strongest negative correlation of -0.48. Despite the fact that there is a modest negative correlation between bean yield and CDD, CDD can be utilized as a predictor of bean yield due to the substantial Granger causality test that was performed at a 95% confidence level.

ACKNOWLEDGMENTS

The authors are grateful to the Rwanda Meteorology Agency and the Ministry of Agriculture and Animal Resources (MINAGRI) for providing data. The authors thank the Expert Team on Climate Change Detection and Indices (ETCCDI) for making R-ClimDex® software available for free.

CONFLICT OF INTEREST

There is no potential for a conflict of interest among the authors.

REFERENCES

Granger, C. W. J. (1969). Investigating Causal Relations by Econometrics Models and Cross-Spectral Methods, *Econometrica*, **37**(3): 424-438. DOI:10.1787/5js33lfw0xxn-en.

- Caesar, J., Alexander, L. V. and Trewin, B. (2011). Changes in Temperature and Precipitation Extremes over the Indo-Pacific Region from 1971 to 2005, *Int. J. Climatol*, **31**(6): 791–801. DOI:10.1002/joc.2118.
- Duan, W., He, B., Takara, K., Luo, P., Hu, M., Alias, N. E. and Nover, D. (2015). Changes of precipitation amounts and extremes over Japan between 1901 and 2012 and their connection to climate indices, *Clim Dyn*, **45**: 2273–2292. DOI: 10.1007/s00382-015-2778-8.
- Esayas, B., Simane, B., Teferi, E., Ongoma, V. and Tefera, N. (2018) Trends in Extreme Climate Events over Three Agroecological Zones of Southern Ethiopia. *Advances in Meteorology*, 1–17. DOI:10.1155/2018/7354157.
- FAO. (2019). FAOSTAT-CROPS. Food and Agricultural Organization of the United Nations, Retrieved October 9(2019): <http://www.fao.org/faostat/en/#data/QC>.
- IPCC. (2007). Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, Geneva, Switzerland, 104pp.
- Karki, R., Hasson, S ul., Schickhoff, U., Scholten T, Böhner J. (2017). Rising Precipitation Extremes across Nepal, *Climate*, **5**(1): 4. DOI: 10.3390/cli5010004.
- Klein T., Albert, M. G, F. and Zwiers W. (2009) WMO Guidelines on Extremes Guidelines on Analysis of Extremes in a Changing Climate in Support of Informed Decisions, *Climate Data and Monitoring (WCDMP-No. 72)*:52.
- Kurecic, P. and Kokotovic, F. (2017). The Relevance of Political Stability on FDI: A VAR Analysis and ARDL Models for Selected Small, Developed, and Instability Threatened Economies, *Economies*, **5**(3): 22. DOI:10.3390/economies5030022.
- Liang, X. S. (2013) The Liang-Kleeman Information Flow: Theory and Applications, *Entropy*, **15**(1): 327–60. DOI: 10.3390/e15010327.
- Lloyd-Hughes, B. and Saunders, M. A. (2002). A drought climatology for Europe, *Int. J. Climatol*, **22**(13): 1571–1592. DOI:10.1002/joc.846.

- Mann, H. B. (1945). Nonparametric Tests Against Trend, *Econometrica*, **13**(3): 245. DOI:10.2307/1907187.
- Mikova, K., Makupa, E. and Kayumba, J. (2015). Effect of Climate Change on Crop Production in Rwanda, *Earth Sciences*, **4**(3): 120. DOI: 10.11648/j.earth.20150403.15.
- MINAGRI. (2018). Ministry of Agriculture and Animal Resources. Strategic Plan for Agriculture Transformation 2018-2024.
- Muhire, I. (2015). Climate Change and Variability and Their Impacts on the Yields of Major Food Crops. PhD Dissertation, Dept. of Environmental Management, University of Johannesburg.
- Ngarukiyimana, J. P., Fu, Y., Yang, Y., Ogwang, B. A., Ongoma, V. and Ntwali, D. (2018). Dominant Atmospheric Circulation Patterns Associated with Abnormal Rainfall Events over Rwanda, East Africa, *Int J. Climatol*, **38**(1): 187-202. DOI:10.1002/joc.5169.
- Nicholson, S. E. (2018). The ITCZ and the Seasonal Cycle over Equatorial Africa, *Bull. Amer. Meteor. Soc.*, **99**(2): 337-348. DOI: 10.1175/BAMS-D-16-0287.1.
- NISR. (2013). Seasonal Agricultural Survey, In National institute of Statistics of Rwanda, Retrieved from <http://statistics.gov.rw/publication/seasonal-agricultural-survey-report-2013>.
- Sen, P. K. (1968). Estimates of the Regression Coefficient Based on Kendall's Tau, *Journal of the American Statistical Association*, **63**(324): 1379. DOI:10.2307/2285891.
- Stephen, K., Patience, M. and Eliud, B. (2017). Factors Influencing Commercialization of Beans among Smallholder Farmers in Rwanda, The International Center for Tropical Agriculture (CIAT), Rwanda Corresponding, *IOSR Journal of Agriculture and Veterinary Science*, **10**(8): 30-34. DOI: 10.9790/2380-1008033034.
- Zhang, X., Alexander, L. and Hegerl G. C. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data, *Wiley Interdisciplinary Reviews: Climate Change*, **2**(6): 851–870. DOI:10.1002/wcc.147.