Community Perception and Adoption of Extreme Weather-Induced Patterns in Rwanda: A Case of Nyamagabe District, Rwanda

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Community Perception and Adoption of Extreme Weather-Induced Patterns in Rwanda: A Case of Nyamagabe District, Rwanda

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Abstract

Climate change has intensified the frequency and severity of extreme weather events—such as heatwaves, droughts, and heavy rainfall—posing serious threats to livelihoods, ecosystems, and socio-economic stability. Rwanda, like many developing countries, has experienced notable shifts in temperature and precipitation extremes over recent decades, largely attributed to anthropogenic influences. This study examined community perceptions, impacts, and adaptive responses to extreme weather events in Nyamagabe District from 2012 to 2021, with a focus on food security, water availability, and agricultural and socio-economic wellbeing.Using a cross-sectional design, data were collected through 222 household surveys conducted in Tare and Uwinkingi sectors. The sample predominantly comprised farmers (64.4%), small business owners (17.1%), and salaried workers (14.0%), reflecting a strong dependence on natural resources. Time-series data from the Rwanda Meteorology Agency were also utilized to contextualize observed climate trends.Findings reveal significant impacts resulting from climate-induced events, including floods ($p = 0.022$), reduced crop yields ($p = 0.019$), infrastructure damage ($p = 0.003$), and water scarcity ($p = 0.025$). Psychosocial effects such as fear ($p = 0.012$), powerlessness ($p < 0.001$), and sadness ($p = 0.942$) were also reported. In response, communities adopted adaptive strategies, including the use of improved seeds ($p < 0.001$), efficient cooking technologies ($p = 0.003$), agroforestry and reforestation ($p = 0.001$), and improved or sustainable farming techniques ($p = 0.106$). The study indicates limited awareness of human-induced climate drivers and adaptive capacity. It recommends targeted climate education awareness campaigns, the promotion of sustainable practices, livelihood diversification, investment in climate-resilient agriculture, improved access to and utilization of meteorological data, and strengthened collaboration between government and civil society to enhance adaptive capacity. Further research should explore socio-cultural and economic barriers to the adoption of sustainable adaptation strategies.

Key words: *Community, Perception, Adoption, Extreme Weather Induced Pattern*

1. Introduction

Extreme weather events such as heatwaves, droughts, and heavy rainfall are becoming increasingly frequent and severe due to climate change, primarily driven by human activities (Clarke et al., 2022). These events occur rapidly and are inadequately represented by climatological averages, making them challenging to manage (Clarke et al., 2022). Globally, shifts in temperature and precipitation patterns have profound implications on water resources, agriculture, and socio-economic stability (AghaKouchak et al., 2020). Antecedent conditions like soil moisture deficits can intensify such events, highlighting the complex nature of climate extremes (Seneviratne et al., 2012).

The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) indicates that global warming has reached 1.09°C since the Industrial Revolution, primarily due to human activities. This warming is projected to continue until it reaches an average of 1.5°C in the 2030s, regardless of greenhouse gas emissions (IPCC, 2023).

East Africa has experienced nearly double the global warming since pre-industrial times, with major cities experiencing rapid temperature increases (Richardson, Calow, Pichon, New, & Osborne, 2022). People's physical and psychological well-being are negatively impacted by the frequency and intensity of extreme weather events. Therefore, for the past few decades, there has been a significant amount of emphasis focused on extreme weather occurrences and their effects on human health. The most dangerous effect of extreme weather on human health is the premature death of individuals, while there are other effects as well (Ebi & Bowen, 2016). Extreme weather-related fatalities can affect things at both the macro and micro levels. At the micro-level, the death of an individual can bring mental distress to the family members and their loved ones. Moreover, the death of an income-generating individual can have more serious consequences as it can throw the household into a poverty trap. At the macro level, the demographic structure can change if deaths from a particular age or sex are more frequent (Bernai, 2024).

In Rwanda, the annual mean temperature in Kigali City increased by 0.0455°C/year between 1958 and 2010, possibly due to urbanization and population growth. In 2004, water levels decreased significantly, reducing power generation. Rwanda's low-lying eastern region has experienced a rise in mean temperature, unpredictability in drought duration and frequency, environmental and infrastructure damage, and crop output and livestock loss. The northwestern high-elevated area has increased potential for Malaria disease (Safari & Sebaziga, 2023).

Therefore, climate-related disasters in Rwanda disproportionately impact the poor, leading to reduced agricultural productivity, famines, and poverty. The vulnerability of people and natural systems to climate change is determined by exposure and sensitivity, with indirect consequences like decreased productivity and disruption to economic systems resulting from direct effects (Adger, et al., 2007). The purpose of this study is to access how local community of Nyamagabe District of Rwanda adopt and perceive on extreme weather induced pattern and correlation between perception and adoption strategies.

1.1 Research Objectives

1.1.1 General objective

The general objective of this study was to explore the community perception and adoption in response to extreme weather-induced patterns in Nyamagabe District, Rwanda.

1.1.2 Specific objectives

The specific objectives of this study are the followings:

i. To analyze Extreme Weather-Induced Patterns in Nyamagabe district of Rwanda
ii. To Assess Community Perception and Adoption regarding extreme weather-induced patterns
iii. Examine the Relationship Between Extreme Weather-Induced Patterns and Community Perception and Adoption

2. Materials and methods

2.1 Profile of Nyamagabe District

Nyamagabe District is located in the South-West of the Southern Province, surrounded by other districts. It spans 1090 Km2 and is divided into 17 administrative sectors, 92 cells, and 536 villages. The district has an average altitude of 1800-2700 meters and is characterized by jagged and irregular slopes, making soils susceptible to erosion. The hydrograph is divided into two main basins: Mbirurume and Rukarara rivers in the North and Mwogo in the South, with Gihimbi, Nyamugali, and Nkungu as effluents. The district's soil is generally acidic, resulting in low agricultural productivity unless organic and mineral fertilizers are added. Marshlands in Nyamagabe District occupy 681.6 Ha (Nyamagabe district, 2018).

Around 44.8% of Nyamagabe district is covered by forests, with Nyungwe National Park covering 49.2% of the area. This natural forest plays a significant role in local and regional bio-climatic conditions, acting as a sponge that regulates water levels. The park is home to a diverse range of wild animals, primarily primates and birds, and contains numerous ligneous forests. Nyamagabe district is part of the Creter Congo-Nil chain, with an altitude ranging between 1800m and 2700m. The climate is characterized by 1300mm rainfall and temperatures ranging between 110C and 18oC. The district has four main seasons: two dry seasons (June to August and mid-December to January), two rainy seasons (September to mid-December and February to May) (Nyamagabe district, 2018).

The population of Nyamagabe district is predominantly female: 194,776 are women corresponding to 52.4 % of its total population while male is 176,725. Nyamagabe district population is predominantly by rural area 89.1% while urban represents 10.9%. The 11 out of 17 sectors of Nyamagabe district are entirely considered as rural area. The population aged 0-17 represents 43.7 % of the total population of the district, 16-30 years represent 26.8%; the working age population aged 16 and above represents 61.5% of the same population (NISR, 2023).

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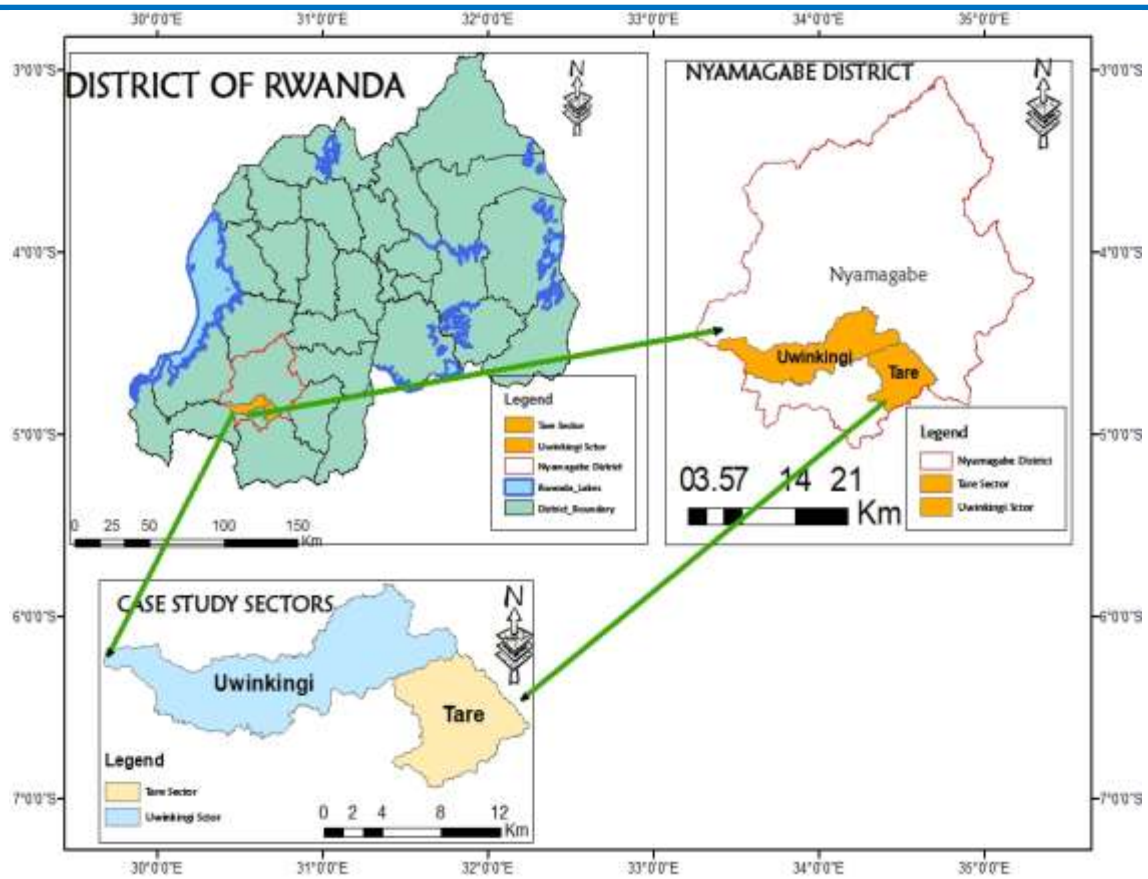

Figure 3. 1 Map of the study area

2.2 Research design and data collection methods

The research employed a cross-sectional design using both quantitative and qualitative methods to analyze community perceptions and adaptation responses to extreme weather patterns in Nyamagabe District, Rwanda. This approach enabled the study to gather data at a single point in time while drawing on both statistical and narrative insights to understand the local impacts of climate variability. Quantitative data included time-series climate records on rainfall and temperatures, while qualitative insights were gathered through household surveys that captured perceptions, experiences, and adaptation strategies related to climate changes observed over a ten-year period (2012–2021).

The study targeted households in the Tare and Uwinkingi sectors of Nyamagabe District, which, according to the 2022 Rwanda Population and Household Census, consist of 6,093 and 6,295 households respectively, totaling 12,388 households. The sample size was calculated using Yamane's simplified formula for sample size determination, with a 7% margin of error (Cochran, 1963). Applying this formula to the total population produced a base sample size of approximately 201 households. To account for potential non-responses and incomplete data, a 10% contingency was added, resulting in a final sample size of 222 households. Proportional allocation was used to distribute the sample across the two sectors, yielding 109 respondents from Tare and 113 from Uwinkingi.

Table 3. 1. Distribution of the respondents in the sectors of the study area

Sector	Household	Sector /Total population x 100	Proportionate sampling	Sample size
Tare	6,093	$\frac{6,093}{12,388}$ x $100 = 49.2\%$	49.2% of 222	109
Uwinkingi	6,295	$\frac{6,295}{12,388}$ x $100 = 50.8\%$	50.8% of 222	113
Total	12,388		222	222

Source: Nyamagabe District (2022)

The sampling process followed a multi-stage approach. Initially, the two sectors were selected randomly. Within each sector, two cells were randomly chosen. Systematic sampling was then employed to select households within those cells. The respondents, typically household heads or their spouses, were selected in collaboration with cell leaders to ensure community representation. The sample considered gender balance and sought a fair distribution between male and female-headed households to reflect the broader demographic composition of the study area (Adam, 2020).

Primary data were collected through a structured household questionnaire administered to the 222 selected households. The questionnaire covered demographic characteristics, perceptions of climate variability, and household-level adaptation strategies. Both close-ended and a few open-ended questions were included to balance quantifiable responses with qualitative insights. Data collection was facilitated using KoboCollect, a digital mobile data-gathering tool that ensured real-time input and minimized data entry errors.

Secondary data comprised daily time-series climate data from the Rwanda Meteorology Agency, specifically from Gikongoro Meteorological Station, selected for its proximity and relevance to the study area. The data set covered the period from 2012 to 2021 and included daily rainfall totals and maximum and minimum temperatures. This information was used to identify trends and patterns in climate variability, allowing the study to correlate meteorological changes with household perceptions and adaptive behavior.

2.3 Data analysis and ethical considerations

The study employed a range of data analysis techniques to examine socio-economic and climate-related variables. Socio-economic data collected from households were analyzed using STATA 13, and the results were exported to Excel for the creation of tables and graphs. Climate data, including rainfall and temperature trends over a ten-year period (2012–2021), were analyzed using the R software package. Data from the Nyamagabe (Gikongoro) Meteorological Station, chosen for its proximity to the study area, were used to support this analysis. Additionally, regression and correlation analyses were conducted to explore relationships between variables.

To ensure data quality, the study incorporated validity and reliability measures such as expert review, Cronbach's alpha, and test-retest methods. Ethical considerations were strictly observed, with informed consent obtained, participant confidentiality protected, and cultural sensitivity maintained throughout the research process. Participants were given the right to withdraw at any point, and community leaders were involved to ensure transparency and respect.

3. Results

3.1 Demographic and Socio-economic characteristics of the respondents

This sub-section emphasizes demographic and socio-economic characteristics of the household that play important role in perceptions and adoptions of extreme weather induced pattern such as sectors, age, gender, household size, marital status, education level, employment status and habitant duration in sector.

Table 3.1. Demographic characteristics of the respondents

Parameter	Valid	Frequency	Percentage
Gender	Female	118	53.15
	Male	104	46.85
	Total	**222**	**100**
Marital status	Widowed	10	4.50
	Single	8	3.60
	Married	204	91.9
	Total	**222**	**100**
Education level of respondents	Not completed primal education	95	42.8
	Primary school	59	26.6
	Secondary school	54	24.3
	TVET	2	0.9
	College and university	12	5.4
	Total	**222**	**100**
Age of the respondent	23 to 30	27	12.2
	31 to 60	162	72.9
	61 and above	33	12.2
	Total	222	100
Occupation of the respondents	Farmer	143	64.4
	Small business	38	17.1
	Salary job	31	14.0

Parameter	Valid	Frequency	Percentage
	Casual job	8	3.6
	Student	2	0.9
	Total	**222**	**100**
Family size	1 to 3	67	30.2
	4 to 6	145	65.3
	7 to 9	10	4.5
	Total	**222**	**100**
Period of respondents lived in Nyamagabe district	Below 10 years	21	9.5
	11 to 30 years	91	41.0
	31 to 60 years	97	43.7
	Above 60 years	13	5.9
	Total	**222**	**100**

Source: Primary data, 2024

The table ***(Table 3.1)*** present the demographic and socio-economic characteristics of survey respondents: The gender distribution is balanced, with 53.15% female and 46.85% male respondents, ensuring a diverse range of perspectives from both genders. The study primarily consists of married, with 91.9% of respondents being married, followed by widowed (4.50%) and single (3.60%). Gender significantly influences household decision-making, with male-headed households being more likely to adopt new technologies and engage in risky businesses (Orser & Riding, 2018; Ndiritu, Berresaw, & Shiferaw, 2014). Studies have shown that gender also affects adoption decisions related to weather patterns and soil and water conservation measures. However, having a female head may negatively impact these decisions due to traditional social barriers, as women may have limited access to information and resources (Mersha & Laerhoven, 2016; Khatibi, Dedekorkut-Howes, Howes, & Torabi, 2021). The study conducted by (Aelst & Holvoet, 2016) stated that married households are more aware of and resilient to extreme weather patterns and climate change adaptation measures than single, divorced, separated, or widowed households, and that this makes the intersectionality approach to gender and climate change policy imperative.

The 42.8% of the respondents did not complete Primary education; 26.6% completed Primary education; 24.3% completed secondary school education; 0.9% pursued technical and vocational education and training (TVET); and only 5.4% pursued college and university education. Accordingly, the likelihood of adjusting to climate change is increased when the head of the household has more education. Additionally, studies have demonstrated that farmers who possess higher levels of knowledge are more inclined to adopt adaptation measures compared to those who do not (Komba & Muchapondwa, 2018).

The age distribution of the respondents is concentrated in the 31 to 60 age group, comprising 72.9% of the respondents while age group of more than 61 years old are 12.2%. The family size is comprising of 4 to 6 has 65.3%, followed by 1 to 3 members (30.2%). The majority of respondents are farmers (64.4%), followed by small business owners

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(17.1%) and salary jobs (14.0%). The dominant occupation as farming suggests a study population with a significant connection to the land and potentially vulnerable to extreme weather events. It was shown that employment status has a significant role in determining decisions on how to adapt to climate change, and jobs outside the farm could boost farmers' income and help them deal with the negative effects of climate change (Azizi-Khalkheili, Aenis, Menatizadeh, & Zamani, 2020). The majority of respondents (90.6%) have lived in Nyamagabe district for more than 10 years, providing a historical perspective on community changes and adaptations to extreme weather events.

3.2 Extreme weather-induced patterns

The first objective of our study is to analyze the extreme weather induced patterns of Nyamagabe for a decade varying from 2012 to 2021.

3.2.1 Rainfall analysis in Nyamagabe district

3.2.1.1 Total rainfall and rainfall intensity analysis from 2012 to 2021

Total rainfall distribution in Nyamagabe district from 2012 to 2021, as observed at the Gikongoro meteorological station, portrays notable fluctuations alongside visible trends.

The following figure shows the historical total precipitation distribution plot from 2012 to 2021 and associated anomaly plot at Gikongoro metrological.

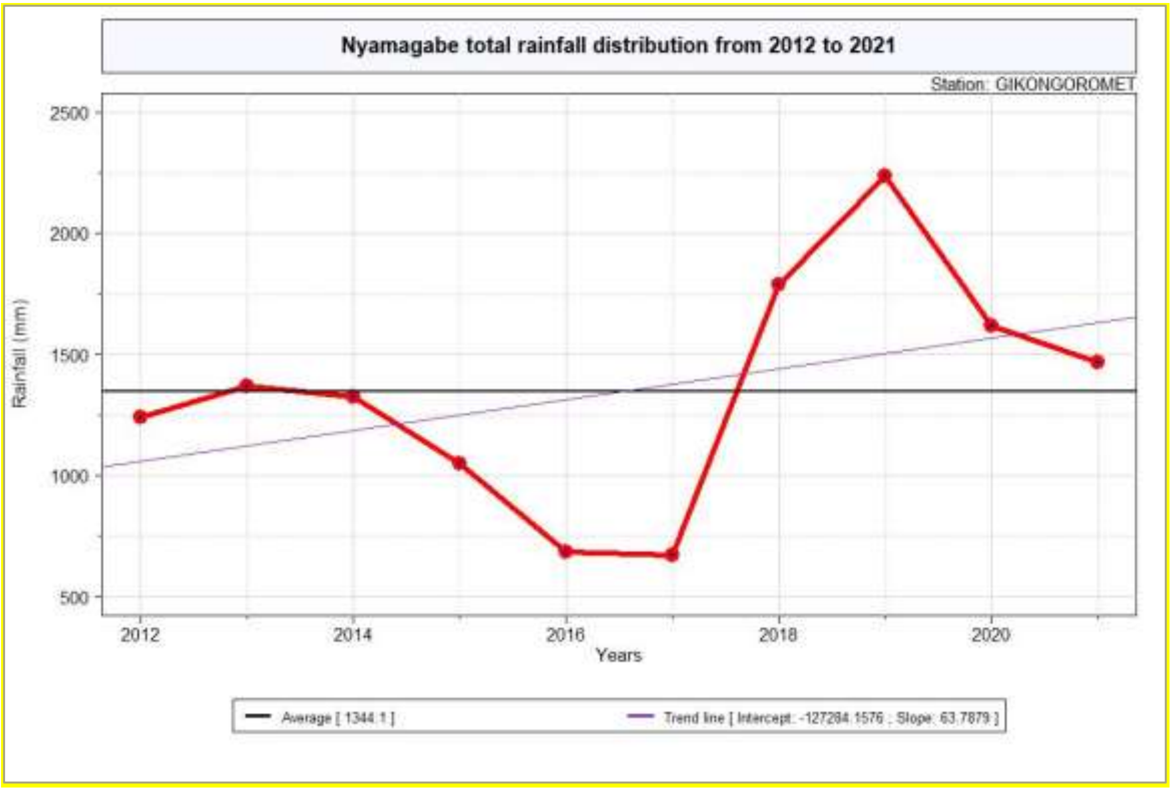

Figure 3.1. Total rainfall distribution in Nyamagabe from 2012 to 2021

Source: Meteo Rwanda, 2024

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Note: The data shows an upward trend leading to a peak of around 2500mm in 2019, followed by a subsequent downward trend to approximately 460mm in 2016 and 2017. Despite these fluctuations, the overall average stands at 1344.1mm. The trend line analysis, with an intercept of -127284 and a slope of 63.7879, underscores a general inclination towards increased rainfall levels over the decade. The upward trend observed until 2019 indicates potentially wetter conditions, while the subsequent decline underscores the variability inherent in rainfall distribution in 2016 and 2017.

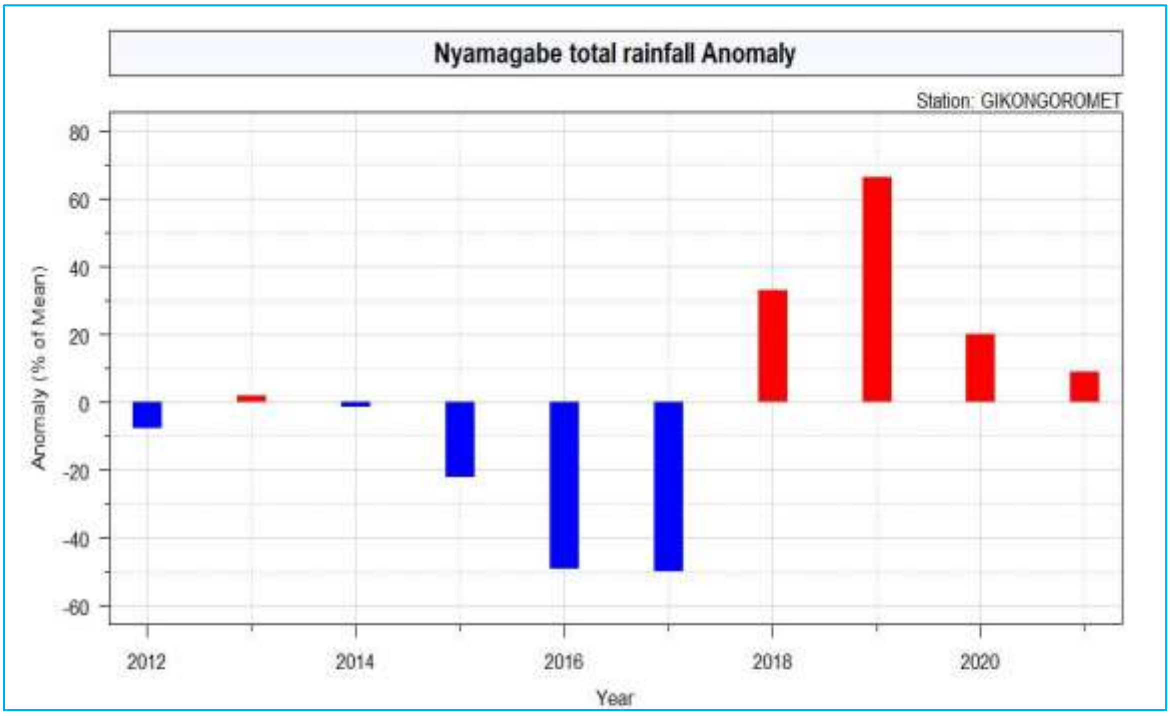

Figure 3. 2. Nyamagabe total rainfall anomaly plot

Source: Meteo Rwanda, 2024

Note: As shown on the **Figure 3.2**, Total rainfall anomalies refer to the difference between the observed total rainfall for a specific period and the long-term average or expected total rainfall for the same period. It indicated whether the observed rainfall during a certain period was above or below what is typically expected for that time frame. A positive anomaly (in red) suggests above-average rainfall in 2018, 2019, 2020, and 2021, while a negative anomaly (blue) indicates below-average rainfall in 2015, 2016, and 2017.The rainfall intensity for Nyamagabe district from 2012 to 2021 at the Gikongoro meteo station was analyzed using data from 2012 to 2021. This equation indicates a general upward trend in rainfall intensity over the given period, as evidenced by the positive slope (0.0615). Firstly, the average rainfall intensity over this period is approximately 3.8959. The trend line equation provided is:

Rainfall=−120.2196+0.0615×YearRainfall=−120.2196+0.0615×Year

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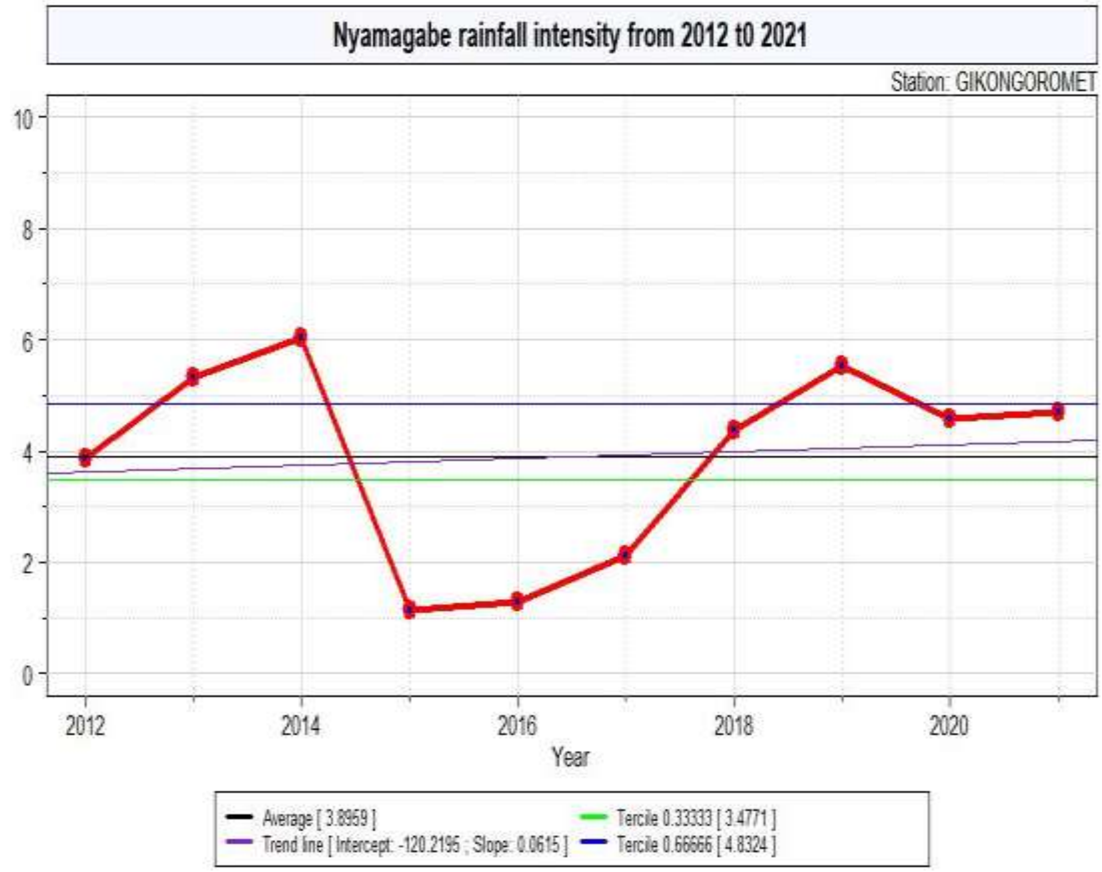

Figure 3.3. Nyamagabe rainfall intensity plot from 2012 to 2021

Source: Meteo Rwanda, 2024

Note: As shown in graph below; The intensity of a substance has fluctuated over time, with a peak in 2012 at 5.47 and a decrease in 2015 to 1. The intensity then increased to 5.5 in 2013, then to 6. In 2016, it was 1.2, then to 2.4, then to 4.5 in 2018, then to 5.7 in 2019, then to 4.8 in 2020, and finally to 4.9 in 2021, maintaining a high intensity. The intensity fluctuated from a low of -1 to a high of 5.7, indicating a fluctuating trend. Increase from 2017-2021. Overall, there is a positive trend in rainfall intensity for Nyamagabe district, with occasional fluctuations.

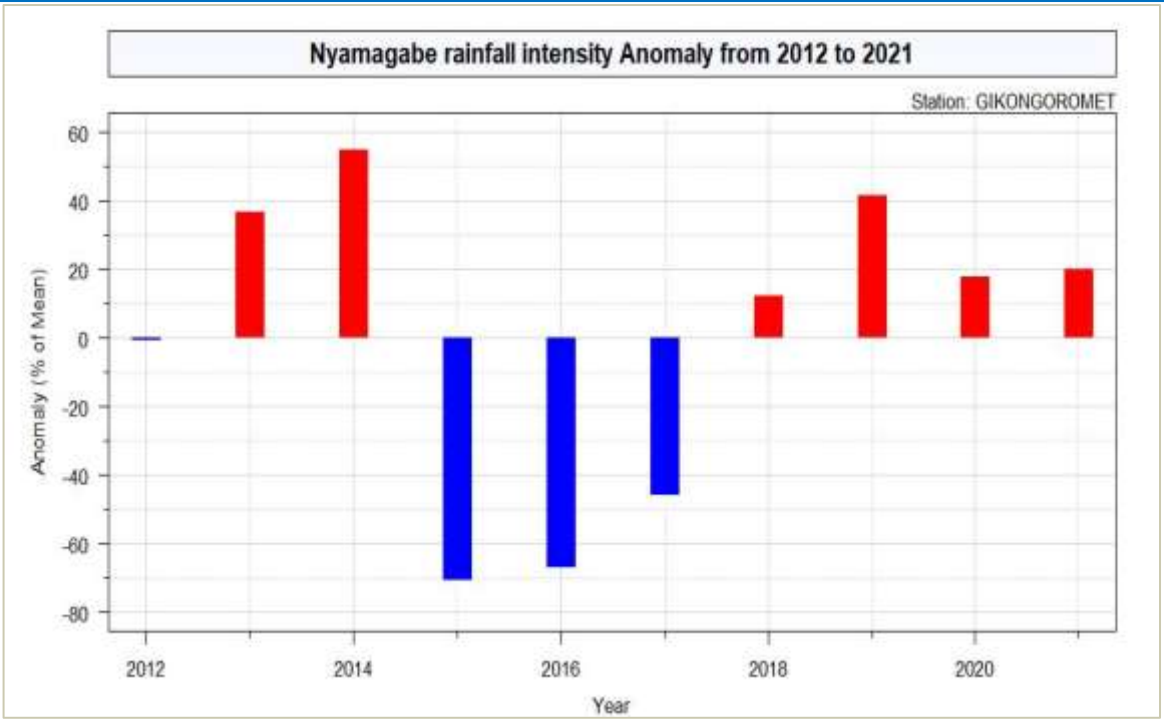

Figure 3.4. Nyamagabe rainfall intensity anomaly plot from 2012 to 2021; Source: Meteo Rwanda, 2024

As shown in the Figure 3.4, the Nyamagabe rainfall intensity anomaly from 2012 to 2021 refers to the variation in rainfall intensity observed in Nyamagabe district during this period compared to the long-term average or expected intensity for the same timeframe. It quantifies whether the actual rainfall intensity in each year is higher or lower than what would typically be anticipated based on historical data. A positive anomaly marked in red indicates above-average intensity in 2013, 2014, 2018, 2019, 2020, and 2021, while a negative anomaly indicated in blue signifies below-average intensity. Tracking these anomalies provides insights into the temporal variability of rainfall intensity and its impact on local weather conditions and ecosystems.

3.2.1.2 Precipitation decile from 2012 to 2021

The Nyamagabe precipitation decile 3 months from 2012 to 2021 is a three-month interval ranked from lowest to highest, divided into ten equal parts, each representing 10% of the data points. Decile 3 is the middle decile, where precipitation falls between the 20th and 30th percentiles of the distribution for each three-month period.

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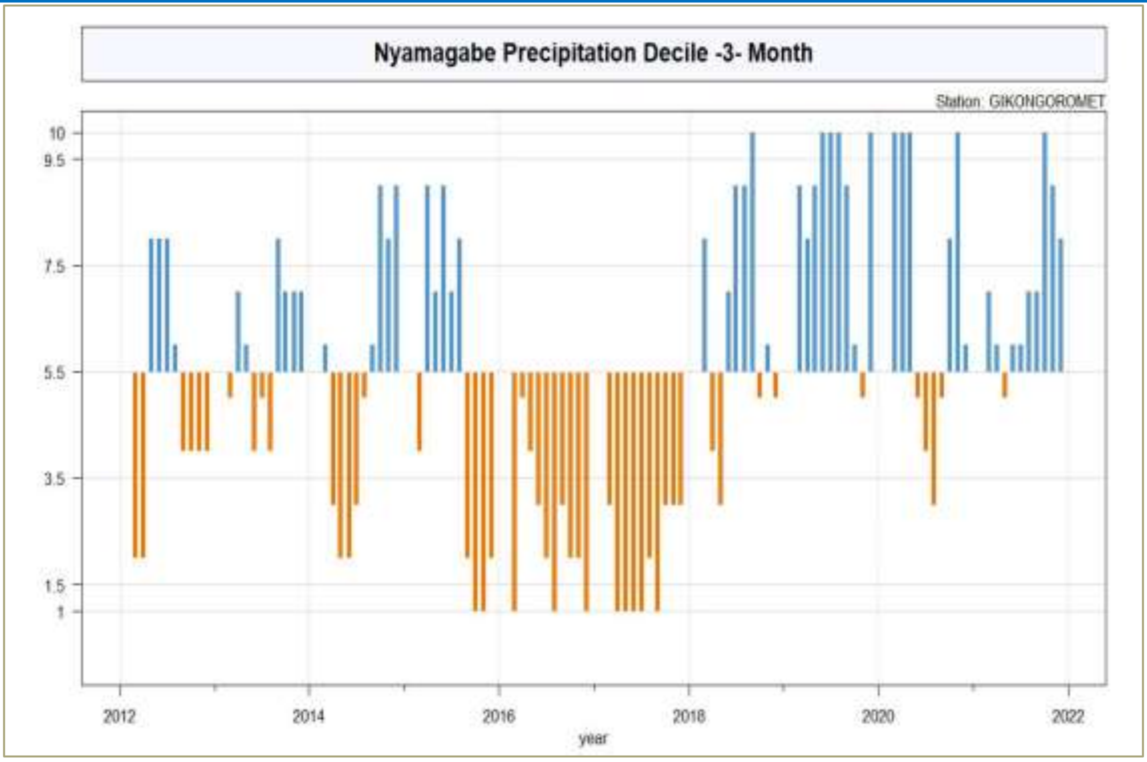

Figure 3. 5. Nyamagabe Precipitation decile plot from 2012 to 2021

Source: Meteo Rwanda, 2024

The 12-month Standardized Precipitation Index (SPI) in Nyamagabe district from 2012 to 2021 measures precipitation anomalies over a 12-month period. It indicates the deviation from the long-term average for that time frame. Positive SPI values indicate wetter conditions, while negative SPI values indicate drier ones. Monitoring the SPI helps assess drought severity and duration, helping in water resource management, agriculture, and disaster preparedness in Nyamagabe district.

3.2.1.3 Standardized precipitation index in Nyamagabe district from 2012 to 2021

Based on the provided SPI values for Nyamagabe district at Gikongoro Metrological Station from 2012 to 2021, here's an interpretation: April, May, and November 2013: These months experienced above-average precipitation, indicating wetter conditions compared to the long-term average. Whole months of 2014 and 2015: These years saw consistently above-average precipitation throughout, suggesting a prolonged period of wetter conditions. Starting from June 2017 to 2021: Similar to previous years, these periods also exhibited above-average precipitation, indicating sustained wet conditions, with a particularly high magnitude in 2020.

June to September 2014, September and October of 2015: These months experienced below-average precipitation, indicating drier conditions than usual. This could lead to concerns such as water scarcity, reduced agricultural productivity, and potential drought impacts. Whole months from 2016 to June 2018: These years exhibited consistently below-

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average precipitation, indicating an extended period of dry conditions, with high magnitude in 2017. This prolonged dry spell could have adverse effects on agriculture, water availability, and ecosystems.

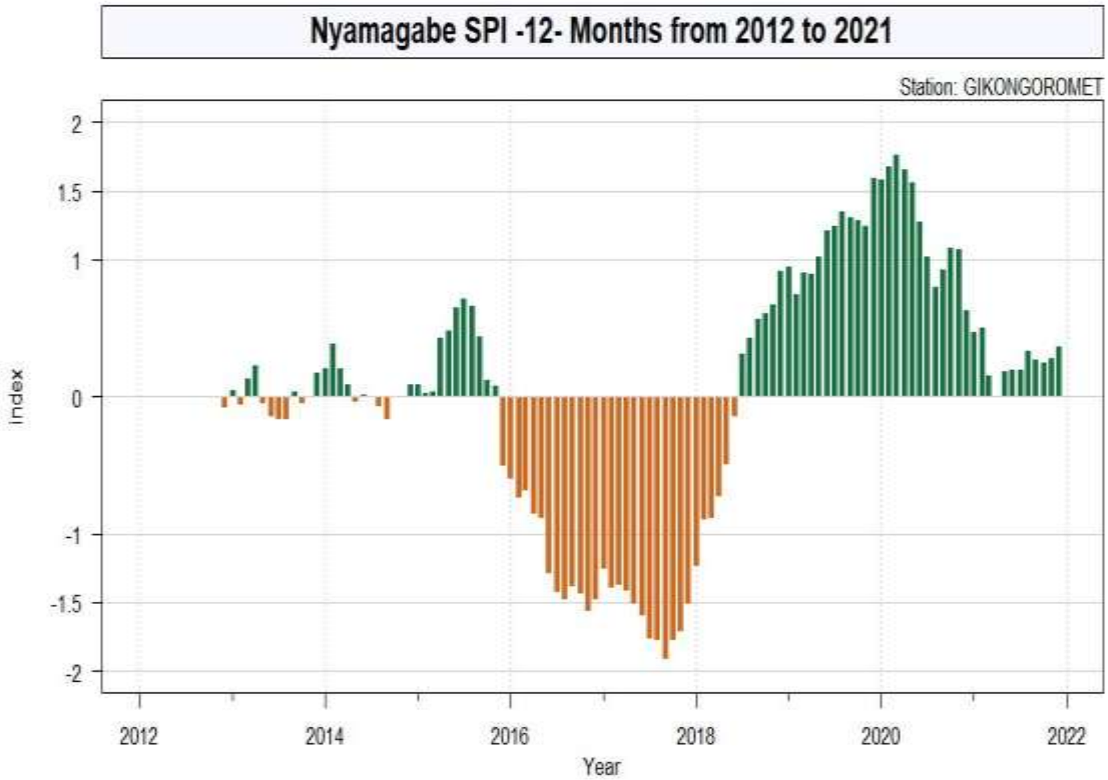

Figure 3.6. Nyamagabe SPI -12- Months plot from 2012 to 2021

Source: Meteo Rwanda, 2024

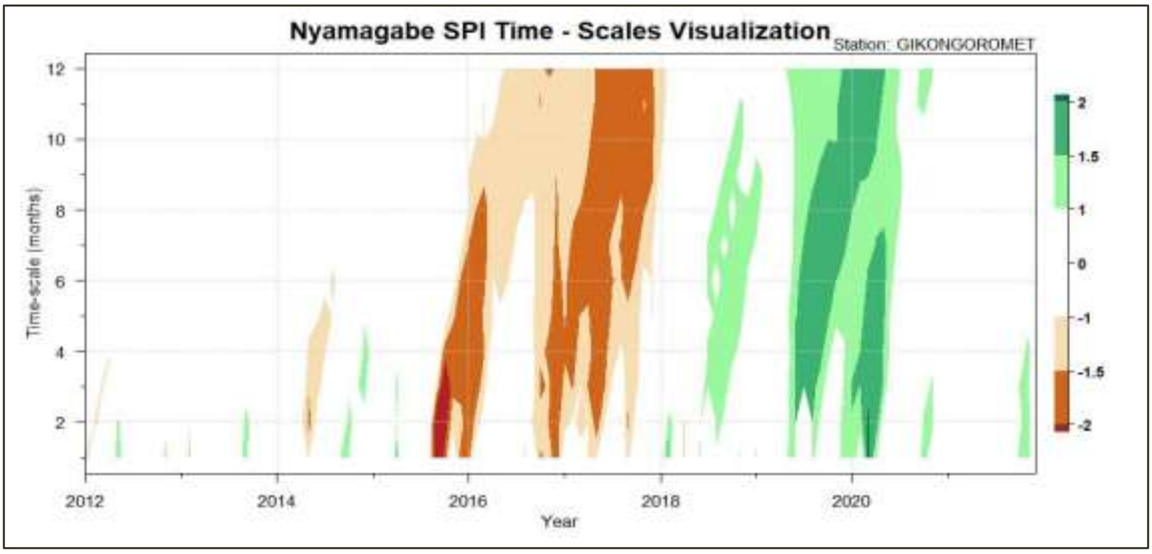

Figure 3.7. Nyamagabe SPI time scale visualization

Source: Meteo Rwanda, 2024

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The Standardized Precipitation Index (SPI) time scale visualization for Nyamagabe district indicates different precipitation levels. SPI Values ≥ 2.00: Extremely Wet - Indicates periods of exceptionally high precipitation, suggesting extremely wet conditions, which could lead to flooding or waterlogging. SPI Values between 1.50 and 1.99: Severely Wet - Represents significantly above-average precipitation, indicating severely wet conditions that may pose risks of flooding or water-related hazards. SPI Values between 1.00 and 1.49: Moderately Wet - Signifies above-average precipitation, suggesting moderately wet conditions that are generally beneficial for agriculture and water resources. SPI Values between -0.99 and 0.99: Near Normal - Reflects precipitation levels close to the long-term average, indicating near-normal conditions with no significant deviations from expected rainfall patterns.

SPI Values between -1.00 and -1.49: Moderately Dry - Indicates below-average precipitation, suggesting moderately dry conditions that may lead to reduced water availability and agricultural productivity. SPI Values between -1.50 and -1.99: Severely Dry - Represents significantly below-average precipitation, indicating severely dry conditions that could result in drought impacts on agriculture, water resources, and ecosystems. SPI Values ≤ -2.00: Extremely Dry - Indicates periods of exceptionally low precipitation, suggesting extremely dry conditions, which may lead to severe drought conditions and associated socio-economic impacts.

3.3 Temperature analysis in Nyamagabe district

3.3.1 Monthly temperature analysis of Nyamagabe district

The Figure 3.8 summarize the monthly temperatures observed in Nyamagabe district from January to December. Temperature observed include Maximum daily temperature and minimum daily temperatures. Nyamagabe, Rwanda experiences a variety of weather patterns throughout the year.

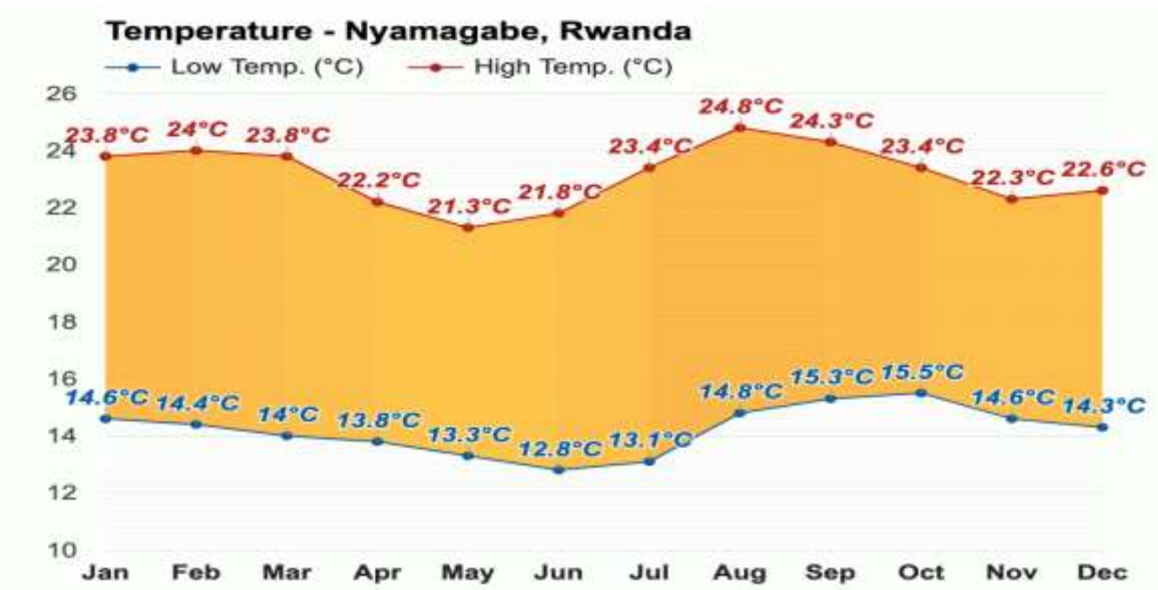

Figure 3.8. Monthly temperature analysis of Nyamagabe district

Source: Meteo Rwanda, 2024

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3.2.3 Temperature extreme analysis in Nyamagabe district

The study examines the maximum and minimum temperature probability of exceedance in Nyamagabe district from January 2012 to December 2021 using time series maximum and minimum temperature data from the Gikongoro metrological station provided by the Rwanda Metrological Agency. The maximum temperature probability of exceedance is found to be 25.92911, with a p-value of 0.7588704 and a coefficient of determination of 0.01691725. The minimum temperature probability of exceedance is 1304.57, with a p-value of 0.553429 and a coefficient of determination of 0.06150059. The intercept represents the minimum value when the independent variable is zero, and the p-value indicates the statistical significance of the relationship between time and the minimum temperature probability of exceedance.

The coefficient of determination measures the proportion of the variance in the dependent variable that is predictable from the independent variable, suggesting that time alone may not be a strong predictor. The slope of 29.54844 indicates the rate of change in the minimum temperature probability of exceedance per unit change in time. In summary, the model suggests a starting point of 1304.57, a statistically significant positive relationship with time, a relatively low coefficient of determination, and a positive slope suggesting an increase in the minimum temperature probability of exceedance over time.

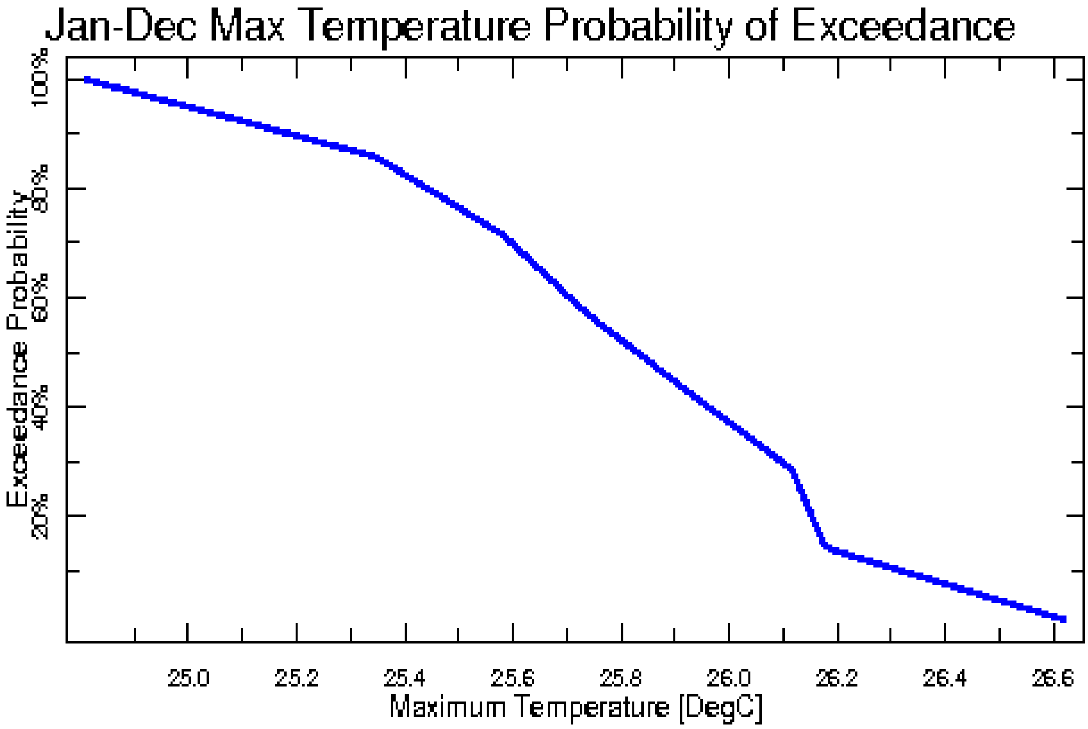

Figure 3.9. Maximum Temperature probability of exceedance plot

Source: Meteo Rwanda, 2024

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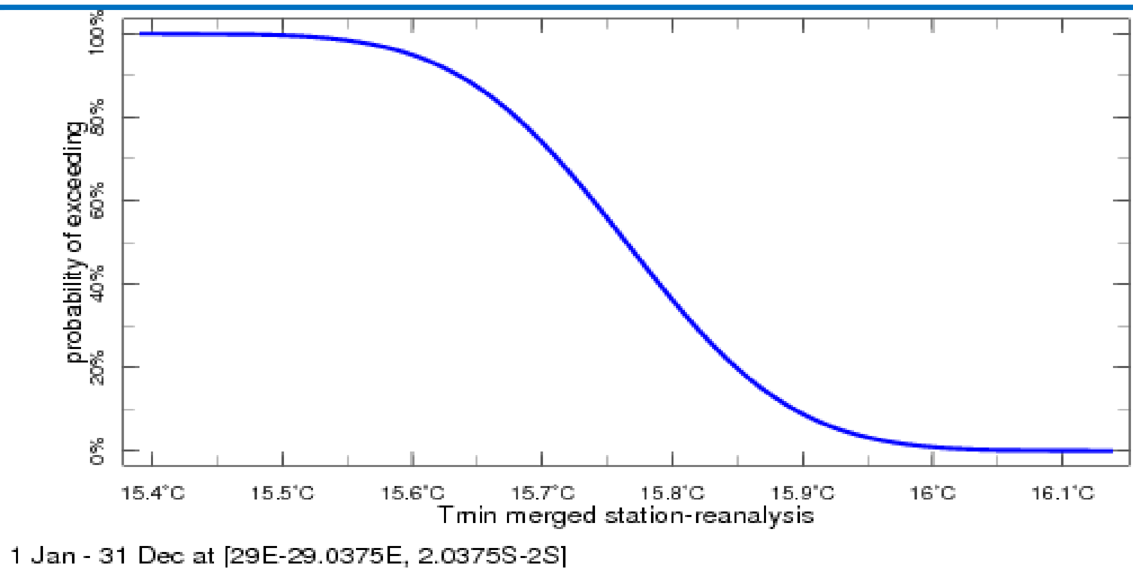

Figure 3.10. Temperature probability of exceedance plot;

Source: Meteo Rwanda, 2024

The models for maximum and minimum temperature probability of exceedance in Nyamagabe district show limited predictability, suggesting that factors beyond time may influence temperature probabilities. The lack of statistical significance in p-values suggests caution in attributing changes solely to time. To understand extreme weather-induced patterns, consider local climate drivers, geographical features, and global climate phenomena.

3.4 Community perception and adoption to extreme weather induced pattern

3.4.1 Community Knowledge and Awareness of extreme weather-induced pattern

Among the 222 respondents to the study, 86.5% of them are aware of extreme weather patterns, while 79.8% have experienced these effects in their households. As summarized in the following **Table 3.2**, 92.8% associate changes in weather patterns with erratic rainfall, 75.7% associate them with hotter temperatures, and 49.5% associate them with the unpredictable nature of seasons. 60.4% of respondents associate extreme changes in weather patterns with an increase in diseases and health-related concerns within the community. 73.9% heard the impact of extreme weather patterns in the context of soil erosion, 51.8% with flooding that causes house destruction, 6.3% with drought, and 38.7% with public infrastructure destruction. 57.2% associate extreme weather with an increased risk of specific diseases like malaria. In this study, it has been highlighted that the awareness of the community of Nyamagabe district in terms of extreme weather-induced patterns is interpreted in terms of the impacts they have heard and the negative impact brought by climate change they experienced.

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Table 3.2. Respondents awareness of extreme weather-induced pattern in their respective sector

Value	Frequency	Percentage
Hotter temperature	168	75.7
Erratic rainfall	206	92.8
Unpredictable seasons	110	49.5
Increases of Diseases	134	60.4
Soil erosion	164	73.9
House destruction	115	51.8
Drought	14	6.3
Destruction of public (Eg: road, hospital,..)	86	38.7
Increases of diseases (Eg: Malaria)	127	57.2
Floods	109	49.1
Deforestation (bushfires)	14	6.3
Swamps and wetland destructions	3	1.4
domestic animal stocks may decline	2	0.9

Source: Primary data, 2024

3.4.2 Cause of extreme weather induced pattern

The study also wanted to know if the communities were aware of the cause of the extreme weather-induced pattern. It revealed that 57.66% do not know the cause of extreme weather-induced patterns, while 41.44% claim to know the cause. For those who know the cause, they highlighted different causes of extreme weather patterns, including forest destruction for charcoal and fuel woods for household cooking, firewood cooking itself, car fuel, an increase in industries that release carbon dioxide into the atmosphere, and soil overexploitation through agriculture, mining, housing, and others. For those who don't know, the study highlighted the need for awareness of campaigns and capacity building.

3.4.3 Experiencing impact of extreme weather induced pattern

This section provides insights into the impact of extreme weather induced patterns reported by household's respondents in Nyamagabe district as shown in **Table 3.3.** Almost all households (97.7%) have experienced a reduction in agricultural yield, while 81.5% of households report a reduction in the quality of their crop yields. (4.5%) and (4.5%) of the households have experienced house destruction and erosion/landslides. Households reported experiencing crop pests and diseases at 17.6%, while 5% relocated and were displaced from their households due to the effects of extreme weather patterns. More than a quarter of households (28.4%) report health impacts, indicating that extreme weather conditions have contributed to the spread of diseases within the community, while 17.6% have experienced water scarcity, which may be attributed to irregular rainfall patterns affecting water sources. (2.7%) report theft and rustling, suggesting that there may be security concerns associated with extreme weather events and About 14.4% of households have experienced a loss of assets, indicating that extreme weather events have economic implications for the community. While the percentage is low, the reported instances of the deaths of people (0.9%) and the loss of animals (14.9%) highlight the serious consequences of extreme weather events on both human and animal life, while 8.1% report issues related to livestock pests and parasites, indicating challenges in maintaining healthy livestock.

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Table 3.3. Impact of extreme weather induced pattern

Experienced Impact	Frequency of respondents	Percentage
Reduction of agriculture yield	217	97.7
Reduction of crop yield quality	181	81.5
House destructions	10	4.5
Erosion and landslides	10	4.5
Crop pest and diseases	39	17.6
Relocation (Displacement of household)	11	5.0
Health impacts (Diseases)	63	28.4
Water scarcity	39	17.6
Theft & rusting	6	2.7
Loss of household assets	32	14.4
Death of peoples	2	0.9
Loss of animals	33	14.9
Livestock pests & parasites	18	8.1

Source: Primary data, 2024

3.4.4 Perception of the severity of extreme weather-induced pattern

Table 3.4. below shows the findings of respondents' perceptions of the severity of extreme weather-induced patterns experienced in their respective households. The results show that a small percentage of respondents (9.9%) expressed uncertainty or indecision, suggesting a need for more information or awareness about the impacts of these patterns. A considerable portion (30.2%) perceived the severity of the extreme weather-induced patterns as low, suggesting minimal impact. The majority (46.4%) perceived the severity at a medium or moderate level, indicating a significant recognition of the impact, while 13.5% perceived the severity as high, indicating a recognition of the significant impact on households and the significant challenge they pose.

Table 3.4. perception of severity of extreme weather induced patterns on households

Value	Frequency	percentage
undecided	22	9.9
Law	67	30.2
Medium	103	46.4
High	30	13.5
Total	**222**	**100**

Source: Primary data, 2024

3.4.5 Community emotional feeling about extreme weather induced pattern

To understand the behavior of community in responses to extreme weather induced patterns, study identified community emotional feelings resulting from those extreme and negative impacts they bring since the emotion feelings also affect the adoption strategies that can be established. The majority of 76.13% expressed feeling of afraid or fearful, which indicates widespread apprehension and concern within the community about the potential impacts of extreme weather events. 33.33% felt powerless, indicating they could not effectively control the situation. 12.61% reported sadness, 11.26% expressed general

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concern or disbelief, reflecting a mix of worry and uncertainty. 7.5% felt confused, indicating a lack of understanding about the causes and implications of extreme weather-induced patterns. 5.25% reported anger, possibly due to frustration or dissatisfaction. 4% expressed hopefulness, believing there are actions to adapt and mitigate the impacts of extreme weather-induced patterns. 3% reported being only curious about the future, suggesting a detached or observational stance towards the potential outcomes of extreme weather events.

Table 3.5. community emotional feeling on impact brought by extreme weather induced patterns

Value	Frequency	Percentage
Fearful/afraid	169	76.13
Powerless e.g.: I can't do anything	74	33.33
Sad i.e. we might lose our culture & lands	28	12.61
Concern/ disbelief	25	11.26
Confused	16	7.5
Angry	12	5.25
Hopeful i.e. we can do some things to adapt	9	4
Curious	7	3.15

Source: Primary data, 2024

3.4.6 Community Adoption to extreme weather induced pattern

Climate change resilience involves proactive measures like resilient agricultural practices, infrastructure construction, early warning systems, and community preparedness. This forward-looking approach minimizes negative impacts while maximizing opportunities, acknowledging climate change, and fostering a more resilient future. In this study, Data indicated a significant portion of the community lacks understanding of the concept of "adoption" concerning extreme weather-induced patterns, with 61.71% responding negatively while 38.29 responded positively. The study analyzed the adaptation strategies of communities to extreme weather-induced patterns in the study area. Different approaches were adopted by respondents as shown in Table 3.6 below.

Table 3.6. Community adoption practices to extreme weather-induced pattern

Community practices	Frequency	Percentage
Use energy saving stoves	191	86
Planted drought flood resister crops	71	32
Agroforestry	80	36
Afforestation reforestation	92	41.4
Constructed strong house, walls,	21	9.5
Planted trees and bushes along houses	64	28.8
On farm water conservation (i.e. terrace, ridge,..)	87	39.2
Installed rain water tank	41	18.5
Crop rotation and use of improved varieties	116	52.3
looked after trees/bushes e.g. watering during drought	23	10.4
Relocation from prone areas	15	6.8
Livelihood diversification	31	14
Stopped wastage of water	20	9
Health insurance	9	4.1
Used modern farming methods	94	42.3
Conserved rationed water	4	1.8
Increased savings	38	17.1

Source: Primary data, 2024

Respondents are adopting energy-saving stoves (86%), modern farming methods (42.3%), and climate-resilient crops (32%), to improve soil health and resilience against extreme weather events. Other adopted approaches include agroforestry for soil and plant conservation (36%), reforestation, and afforestation (41.4%). Other strategies identified include community efforts to restore and expand forest cover, prioritize savings, and implement livelihood diversification. Resilient infrastructure construction was also identified as crucial for protecting lives and property during extreme weather events at 9.5%. However, a small percentage of respondents prioritize tree care during droughts and water conservation practices. Health insurance is being considered, but its inclusion may not address the indirect health impacts of extreme weather events.

3.4.7 Community Thought on perception and adoption to extreme weather pattern

In this study different community thought were collected to have their understanding on perceptions and adoption to extreme weather induced patterns in Nyamagabe district of Rwanda.

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Table 3.7. Community thought on perception and adoption to extreme weather induced patterns

Statement	Agree (%)	Disagree (%)	Unsure (%)
Extreme weather induced pattern is happening	96.8	3.2	0.0
Extreme weather pattern is affecting the people of this sector	97.7	2.3	0.0
Every individual can do something to adapt to extreme weather pattern	62.2	37.8	0.0
Nothing can be done to cope with effect of extreme weather pattern.	42.8	56.3	0.9
Having the information on extreme weather pattern could reduce vulnerability	89.2	10.8	0.0
Capacity building could help to build resilient capacity to effect of extreme	86.9	13.1	0.0
We don't have accurate metrological information	92.3	6.8	0.9
The central/local government are doing things to help us to adapt to extreme weather pattern i.e. in our community.	73.0	2.3	24.8
The central/local government has already consulted us to enable us to identify our areas of concern about cc on our community.	38.7	32.4	28.8
Information regarding to extreme weather induced pattern are available	44.1	37.8	18.0
Civil societies organizations and other institutions are helping us to adopt to effect of climate change	33.3	19.8	46.8

Source: Primary data, 2024

The majority of respondents (96.8%) agree that extreme weather-induced patterns are occurring, indicating a high level of awareness within the community. However, a significant portion (37.8%) disagrees with the notion that every individual can contribute to adapting to these patterns. There is a notable divide on the belief that nothing can be done to cope with the effects of extreme weather patterns. A large majority (89.2%) believe that having information on extreme weather patterns could reduce vulnerability, emphasizing the importance of awareness. A significant portion (86.9%) agrees that capacity building could help build resilience to the effects of extreme weather patterns. However, a substantial number (92.3%) feel they lack accurate meteorological information, highlighting a potential gap in communication or access. The majority (73.0%) believe that the central/local government is taking actions to help the community adapt to extreme weather patterns.

3.4.8 Challenges in adoption strategies to extreme weather induced pattern

The findings present the challenges identified by respondents in Nyamagabe district regarding hindrances to the adoption of strategies for coping with extreme weather-induced patterns which are primarily characterized by financial constraints, lack of awareness, and limited access to essential resources.

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Table 3.8. Challenges in adoption strategies of extreme weather induced pattern

Value	Frequency	Percentage
Limited Financial Resources	160	72.07
Lack of Awareness and Education	143	64.41
Limited Access to Climate Information	14	6.31
Resistance to Change	7	3.15
Inadequate Access to Technology	6	2.7
Vulnerable Agricultural Practices	6	2.7
Geographical landscape	5	2.25
Dependency on Traditional Practices	2	0.9
Land Tenure Issues	2	0.9

Source: Primary data, 2024

As shown in table 3.8: Limited financial resources (72.07%), a lack of knowledge and education (64.41%), restricted access to climate information (6.31%), resistance to change (3.15%), inadequate access to technology (2.7%), vulnerable agricultural practices (2.7%), prone areas in the geographical landscape (2.25%), traditional practices (0.9%), and land tenure issues (0.9%).

3.4.9 Communication channels in regard to extreme weather induced pattern

The findings present data on the types of communication channels used by respondents in study areas for enhancing their perception and adoption strategies toward extreme weather-induced patterns, as highlighted in the table below:

Table 3.9. Communication channels used for extreme weather induced pattern

Communication channels	Frequency	Percentage
Radio	202	90.99
Direct observation	44	19.82
Phone	9	4.05
Computer internet	8	3.6
Community meeting (i.e. Umuganda,..)	8	3.6
TV Channels	7	3.15
Family and neighbors	6	2.7
Churches	2	0.9
NGOs interventions	1	0.45
Local newspaper	1	0.45
Posters	1	0.45

Source: Primary data, 2024

The majority of respondents rely on radio for information on extreme weather-induced patterns, with 19.82% using direct observation. A small percentage use phones, and 3.6% access information through the internet. Community meetings contribute to information sharing, while TV channels and informal networks are used by 3.15% and 2.7% respectively. Religious institutions have a minor role in communication, while NGOs interventions play a limited role at 0.45%. Local newspapers have a low use of 0.45%, and posters have a minor role in conveying information. The use of non-governmental organizations (NGOs) and local newspapers is very low, suggesting a limited influence on communication. Visual aids, such as posters, have a minor role in conveying information about extreme weather events.

3.5 Relationship between community perception and adoption to extreme weather induced pattern

In order to examine the relationship between community perception and adoption of extreme weather-induced patterns, we made the assumption that community adoption decisions are influenced by a variety of factors, including individual awareness and skill levels, perceived risks, communication channels, and the negative effects of extreme weather-induced patterns on people.

3.5.1 Relationship between extreme weather induced patterns and community feelings perceptions

This regression analysis explores the relationship between extreme increases in temperatures and community feelings, with specific emotional states (Fearful/afraid, Powerless, Hopeful, Sad).

Table 3.10. Model summary for Regression analysis of relationship between extreme weather induced patterns and community feeling perception

Source	SS	df	MS	Number of obs	=	222
				F(4, 217)	=	7.69
Model	5.071603	4	1.26790081	**Prob > F**	=	0
Residual	35.79326	217	0.16494591	**R-squared**	=	0.1241
				Adj R-squared	=	0.108
Total	40.86486	221	0.18490889	**Root MSE**	=	0.40614

Source: Primary data, 2024

The regression analysis reveals a significant relationship between extreme weather-induced patterns and community feeling perception. The model explains some of the data's variance, with residuals remaining after accounting for the model. The F-statistic and R-squared coefficients indicate that the model can explain about 12.41% of the variance in community feeling perception. Adjusted R-squared and Root Mean Square Error (RMSE) estimates suggest that the model only explains about 10.8% of the variance.

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Table 3.11. Regression analysis result of relationship between extreme weather induced patterns and community feeling perception

Extreme weather induced patterns	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Fearful/afraid	0.172245	0.068084	2.53	0.012	0.038054	0.306437
Powerless	0.219339	0.060347	3.63	0	0.100396	0.338281
Hopeful	-0.60571	0.21067	-2.88	0.004	-1.02093	-0.19049
Sad	0.006208	0.084525	0.07	0.942	-0.16039	0.172803
_cons	0.562651	0.069968	8.04	0	0.424748	0.700554

Source: Primary data, 2024

Extreme increases in temperatures are associated with increased feelings of fear, powerlessness, hopefulness, and sadness. For fearful or afraid, the coefficient is positive (0.172) and statistically significant with a p-value of 0.012, suggesting that extreme increases in temperatures are associated with an increase in feelings of fear or being afraid. for Powerless; a coefficient (0.219) with a p-value of 0.000, indicating that extreme increases in temperatures are associated with an increase in feelings of powerlessness. Hopeful has a negative and statistically significant coefficient (-0.606) with a p-value of 0.004, suggesting that extreme increases in temperatures may lead to a decrease in feelings of hopefulness. Sad: The coefficient for this variable is positive (0.006), but it is not statistically significant with a p-value of 0.942. This suggests that extreme increases in temperatures do not significantly influence feelings of sadness within the community.

3.5.2 Relationship between extreme weather-induced patterns and strategies adopted by communities to cope with associated effects

This regression analysis examines the relationship between various extreme weather-induced patterns, including extreme rainfall, erratic rainfall, increases in temperatures, flooding, and droughts, and the strategies adopted by communities to cope with associated effects.

Table 3.12. Summary Regression model of analysis of extreme weather induced patterns and community adopted strategies to cope with associated effects.

Source	SS	Df	MS	Number of obs	=	222
				F(11, 210)	=	2.93
Model	7.393441	11	0.672131	**Prob > F**	=	0.0012
Residual	48.10205	210	0.229057	**R-squared**	=	0.1332
				Adj R-squared	=	0.0878
Total	55.4955	221	0.251111	**Root MSE**	=	0.4786

Source: Primary data, 2024

The regression analysis shows that the overall model is statistically significant with a p-value of 0.0012, indicating that at least one independent variable significantly predicts the dependent variable. The R-squared value of 0.1332 indicates that 13.32% of the variance in coping strategies can be explained by extreme weather-induced patterns and other independent variables. The adjusted R-squared value is 0.0878, considering the number of predictors and sample size.

Table 3.13. Regression analysis of extreme weather induced patterns and community adopted strategies to cope with associated effects.

Extreme weather induced patterns	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Uses of improved seeds in agricultures	0.362015	0.0903002	4.01	0	0.1840035	0.540025
Improved farming techniques	0.146598	0.0903142	1.62	0.106	-0.0314404	0.324637
Crop rotations	-0.08431	0.2587265	-0.33	0.745	-0.5943476	0.42572
Improved Cooking technologies	0.303658	0.1025976	2.96	0.003	0.1014046	0.505911
Livelihood diversification	0.202381	0.111413	1.82	0.071	-0.0172498	0.422013
Health insurance	0.072281	0.3139458	0.23	0.818	-0.5466086	0.69117
Agroforest, afforestation and reforestation	0.382576	0.1146956	3.34	0.001	0.1564732	0.608678
_cons	0.082028	0.1071448	0.77	0.445	-0.1291893	0.293245

Source: Primary data, 2024

Uses of Improved Seeds in Agriculture (p = 0.000) with a coefficient of 0.362015. This indicates a significant positive relationship between the use of improved seeds in agriculture and the adoption of coping strategies. Communities use improved seeds in agriculture that are more resilient to the effects of climate change as an adaptive and coping mechanism for extreme weather-induced patterns. Agroforest, Afforestation and Reforestation (p = 0.001) with Coefficient: 0.382576; There is a significant positive relationship between engaging in agroforest, afforestation, and reforestation efforts and the adoption of coping strategies. This implies that environmental conservation measures are linked to better coping mechanisms.

Policies promoting the use of improved seeds in agriculture, adoption of advanced cooking technologies, and environmental conservation efforts like agroforest, afforestation, and reforestation can be encouraged to enhance community resilience to extreme weather events. While factors like improved farming techniques and crop rotations may have

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theoretical benefits, their practical significance in coping mechanisms is uncertain in this context. Further research may be needed to better understand their role.

3.5.3 Examining how community adoption strategies are impacted by patterns caused by extreme weather

The impact of patterns caused by extreme weather on community adoption strategies is investigated through regression analysis.

Table 3.14. Summarize model for Regression analysis of how community adoption strategies are impacted by extreme weather events

Source	SS	df	MS	Number of obs	=	220
				F(13, 206)	=	5.38
Model	13.16193	13	1.012456	Prob > F	=	0
Residual	38.76535	206	0.188181	R-squared	=	0.2535
				Adj R-squared	=	0.2064
Total	**51.92727**	**219**	**0.237111**	**Root MSE**	**=**	**0.4338**

Source: Primary data, 2024

The findings indicate a strong correlation between community adoption strategies and patterns brought about by extreme weather. With an R-squared of 0.2535, these patterns can account for 25.35% of the variance in these strategies. After accounting for the number of predictors in the model, the adjusted R-squared value of 0.2064 offers a more conservative estimate of the variance explained.

Table 3.15. Regression analysis of effect caused by extreme weather induced patterns affects community adoption strategies

Adoption strategies to extreme weather induced patterns	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Drought	0.086856	0.140127	0.62	0.536	-0.18941	0.363123
Floods	0.142162	0.061491	2.31	0.022	0.02093	0.263393
Soil erosion	-0.26923	0.069438	-3.88	0	-0.40613	-0.13233
Reduction of agriculture yield	-0.19507	0.082191	-2.37	0.019	-0.35712	-0.03303
Deforestation	0.220455	0.255422	0.86	0.389	-0.28312	0.724032
Destruction of public infrastructures	0.477185	0.156076	3.06	0.003	0.169473	0.784897
House destruction	-0.21131	0.141851	-1.49	0.138	-0.49097	0.068359
Temperature increases	-0.00131	0.202916	-0.01	0.995	-0.40136	0.398752
Erosion and Landslides	0.254859	0.192443	1.32	0.187	-0.12455	0.634269
Loss of household assets	-0.64323	0.392148	-1.64	0.102	-1.41637	0.129907
Infrastructure Damages	0.074785	0.154751	0.48	0.629	-0.23032	0.379884
Water scarcity	0.796417	0.352639	2.26	0.025	0.101173	1.491661
Health impacts	-0.25649	0.355864	-0.72	0.472	-0.9581	0.445108
_cons	0.62599	0.222926	2.81	0.005	0.186481	1.065498

Source: Primary data, 2024

Floods ($p = 0.022$): Communities tend to adopt strategies in response to floods. Soil erosion ($p < 0.001$): This has a significant negative effect on community adoption strategies, indicating that communities adopt coping mechanisms to mitigate soil erosion. Reduction of agricultural yield ($p = 0.019$): It negatively impacts community adoption strategies. When people experience the loss of agricultural yield, their resilient capacity and livelihood tend to diminish, which later affects adoption strategies for extreme weather-induced patterns. Destruction of public infrastructures ($p = 0.003$): Communities tend to adopt strategies in response to the destruction of public infrastructures caused by extreme weather events. Water scarcity (p = 0.025): It has a significant positive effect on community adoption strategies, suggesting that communities adopt coping mechanisms to deal with water scarcity. Constant term (p = 0.005): The intercept is statistically significant, indicating that even in the absence of extreme weather-induced patterns, there's a baseline level of adoption strategies. The study indicates that communities are highly responsive to floods, soil erosion, agricultural yield reduction, public infrastructure destruction, and water scarcity when adopting coping strategies.

4. Conclusion

In conclusion, This study assessed the demographic and socio-economic characteristics of residents in Nyamagabe District, the patterns of extreme weather events, community perceptions of climate change, and the relationship between perception and adaptation strategies. The findings revealed that the majority of respondents are married, middle-aged, and primarily engaged in farming. With over 90% of respondents having lived in the district for more than a decade, their long-term exposure to environmental changes provides an informed perspective on shifts in local climate patterns. The community's strong ties to land-based livelihoods make them particularly vulnerable to weather-related disruptions.

The climate analysis showed a clear trend of fluctuating extreme weather conditions, with alternating periods of intense rainfall and severe drought. These patterns, supported by the Standardized Precipitation Index (SPI) data, indicate significant climate variability, likely influenced by broader phenomena such as El Niño or La Niña. These conditions have resulted in numerous adverse effects, including soil erosion, crop failure, water shortages, damage to infrastructure, and negative impacts on human and animal health. The frequency and intensity of these events have increased community awareness, with a majority recognizing the human causes of climate change, such as deforestation, use of firewood, and industrial emissions.

Despite high awareness levels (96.8%), the study found that many community members lack access to reliable meteorological information and a clear understanding of adaptation strategies. Emotional responses to climate events—such as fear, sadness, and powerlessness—were prevalent and significantly associated with rising temperatures. Regression analysis confirmed that environmental conservation and sustainable agricultural practices, including the use of improved seeds, afforestation, and clean cooking technologies, positively influenced community adaptation. However, challenges like reduced agricultural yield, water scarcity, and erosion were identified as key barriers to effective adaptation.

Therefore, considering the findings of this study, I would like to recommend enhancing public education on the link between human activities and climate change, and ensuring access to accurate weather forecasts. Community-based adaptation programs should promote sustainable farming and energy practices while building local capacity through partnerships with government institutions and civil society. Lastly, further research is needed to uncover social and economic factors that hinder adaptive behavior despite high levels of climate awareness. These efforts will strengthen resilience and empower communities to respond effectively to extreme weather patterns in Nyamagabe District.

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