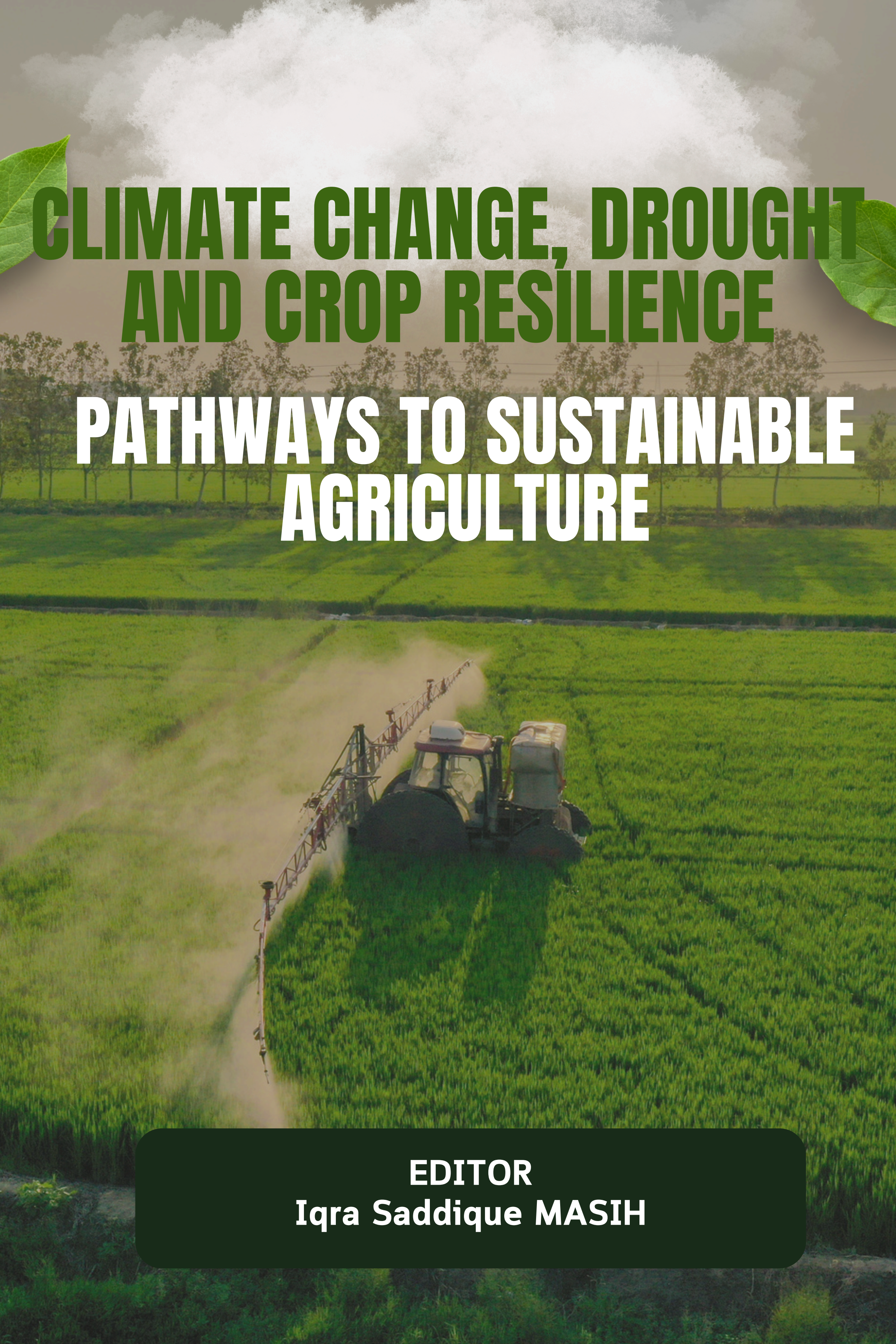
CLIMATE CHANGE, DROUGHT AND CROP RESILIENCE

PATHWAYS TO SUSTAINABLE AGRICULTURE



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PREFACE

This volume presents a multidisciplinary exploration of climate resilience in agriculture, focusing on adaptation strategies, predictive modeling, and sustainable crop development. As climate variability increasingly threatens food and water security, the chapters collectively address the urgent need for data-driven and context-specific solutions.

The first chapter examines how maize farmers in Oyo State, Nigeria, adapt to climate change, highlighting the socio-economic and environmental factors that influence production potential. The second chapter applies a Markov-chain model to analyze dry spell lengths in Benin, offering valuable insights for optimizing crop planning and mitigating climate risks.

Building on these regional studies, the third chapter introduces climate-smart crops as a pathway to sustainable agriculture. It emphasizes the role of crop innovation in enhancing resilience and ensuring food security under changing climatic conditions.

The final chapter explores the application of artificial intelligence in drought forecasting within the Mediterranean context. By integrating advanced technologies into environmental monitoring, it underscores the potential of AI to support proactive water resource management and long-term sustainability planning.

Editorial Team
December 9, 2025
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CHAPTER 1
CLIMATE CHANGE ADAPTATION STRATEGIES ON MAIZE FARMERS PRODUCTION POTENTIALS IN OYO STATE, NIGERIA

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INTRODUCTION

Agriculture remains a cornerstone of livelihoods, economic growth, and sustainable development across Sub-Saharan Africa (SSA). The sector employs more than 60% of the labor force and provides food and income for the majority of rural households, many of whom operate as smallholder farmers (World Bank, 2020). Beyond subsistence, agriculture is the engine of agro-industrial growth, serving as a source of raw materials for manufacturing and contributing significantly to foreign exchange earnings. In Nigeria, agriculture contributes about 23% of the nation's Gross Domestic Product (GDP) and supports the livelihoods of more than 70% of the population either directly or indirectly (National Bureau of Statistics [NBS], 2021). Maize (Zea mays L.) in particular stands out as one of the most important cereals, cultivated across diverse ecological zones of Nigeria. It provides food for humans, feed for livestock, and inputs for industries, while also generating rural employment (IITA, 2019).

Despite its importance, maize production in Nigeria faces multiple challenges, with climate change emerging as one of the most critical. Nigeria's agricultural production is predominantly rain-fed and highly dependent on the variability of rainfall patterns (Ajetomobi & Abiodun, 2010). This dependence makes the sector particularly vulnerable to the effects of climate change, which continues to pose a significant threat to agricultural productivity and food security. According to Awotide et al., (2008), climate and soil resources largely determine the output of maize and other crops, making any changes in these parameters crucial for agricultural outcomes. Variability in climatic conditions directly and indirectly affects the production of maize, one of Nigeria's most important staple crops (Ajetomobi et al., 2011). Maize (Zea mays L.) is a principal cereal crop widely cultivated across all ecological zones in Nigeria and serves as a major source of carbohydrates, animal feed, and raw materials for agro-industrial processes (IITA, 2020). In Oyo State, maize is central to household food security and rural incomes, with smallholder farmers accounting for the bulk of its production. Climate variability refers to the short-term fluctuations in the mean state of the climate and other related statistics, such as the frequency and intensity of extreme events across temporal and spatial scales beyond individual weather occurrences (Planton, 2013).

In contrast, climate represents the long-term patterns of weather, measured by assessing variations in temperature, humidity, atmospheric pressure, wind, precipitation, and other meteorological variables over extended periods (IPCC, 2021). While weather describes short-term atmospheric conditions, climate reflects a region's average conditions over decades or centuries. This distinction is particularly important when assessing agricultural risks and designing adaptation strategies.

The impacts of climate change on agricultural crop production vary across locations and crop types (Müller et al., 2011). Rising temperatures, for example, can significantly reduce crop yields in many parts of the world (Schlenker & Lobell, 2010; Gohari et al., 2013), although certain regions might benefit from warmer and wetter conditions under specific scenarios (Chavas et al., 2009). The effects of climate change include rising sea levels, changes in the timing, intensity, and distribution of precipitation, alterations in temperature patterns, and an increase in the frequency and severity of extreme climatic events such as floods, droughts, and storms (IPCC, 2007; Sultan & Gaetani, 2016). These changes have led to shifts in land and water management practices, which have, in turn, affected agricultural productivity across developing nations (Kandji et al., 2006). The agricultural sector in sub-Saharan Africa (SSA) is particularly exposed to climate-related shocks due to its reliance on rain-fed farming, limited irrigation infrastructure, and low adaptive capacity (Niang et al., 2014; FAO, 2023).

Despite contributing only minimally to global greenhouse gas emissions. Africa accounts for less than 4% of annual global CO_2 emissions African countries are expected to suffer disproportionately from the adverse effects of climate change (Medugu, 2008; FAO, 2016). This phenomenon is often cited in economics as a classic example of negative externalities and cost externalization, whereby the environmental costs of industrial activities in developed countries are borne by less developed nations. Nigeria is no exception. Climate change threatens to exacerbate food insecurity and undermine rural livelihoods, particularly for smallholder farmers (Nwafor et al., 2011). In Oyo State, erratic rainfall patterns, prolonged dry spells, and increased incidence of pests and diseases have been reported to affect maize yields (Ayanlade et al., 2017; NIMET, 2022).

Such adverse impacts, if left unaddressed, could jeopardize Nigeria's progress toward achieving Sustainable Development Goal (SDG) 2 on zero hunger. Maize production in Nigeria has grown steadily over the last two decades, yet yields remain below potential due to climate-related constraints and poor access to improved technologies (FAOSTAT, 2022). In Oyo State, maize farmers face multiple challenges including declining soil fertility, inadequate extension services, limited access to credit, and weak institutional support (Olayide et al., 2016). Climate change compounds these challenges by increasing production risks, lowering returns on investment, and reducing household welfare. Given maize's role as a major staple crop and source of income in Nigeria, understanding farmers' perceptions and adaptation strategies to climate change is critical for developing effective interventions.

Adaptation defined as the process of adjustment to actual or expected climate and its effects is essential to minimize vulnerability and exploit potential benefits (Adger et al., 2005; IPCC, 2021). Farmers' adaptive responses often include changes in planting dates, crop diversification, soil conservation techniques, irrigation practices, and the adoption of drought-resistant crop varieties (Deressa et al., 2009; Kurukulasuriya & Mendelsohn, 2008). However, the extent and effectiveness of these strategies depend on farmers' socio-economic characteristics, access to information, land tenure security, and institutional support (Below et al., 2012). Studies have shown that younger, more educated farmers with greater access to credit and extension services are more likely to adopt improved adaptation practices (Maddison, 2007; Hassan & Nhemachena, 2008). Conversely, resource-constrained farmers may be unable to implement effective measures, thereby increasing their vulnerability to climatic shocks. In Nigeria, various policy initiatives have been introduced to address the impacts of climate change on agriculture. The National Adaptation Strategy and Plan of Action on Climate Change for Nigeria (NASPA-CCN) provides a framework for integrating climate change adaptation into national development plans (Federal Ministry of Environment, 2011). Similarly, the Agricultural Promotion Policy (2016–2020) emphasizes climate-smart agriculture as a means of enhancing resilience in the sector.

However, the effectiveness of these policies depends on their implementation at the grassroots level and the active participation of smallholder farmers (Akinsanmi et al., 2020). In Oyo State, extension services and non-governmental organizations have been involved in training farmers on climate-smart practices, but the coverage and sustainability of such programs remain limited. The theoretical foundation of climate change adaptation in agriculture draws on concepts of vulnerability, resilience, and risk management (Turner et al., 2003; Folke et al., 2010). Vulnerability is determined by a combination of exposure to climatic hazards, sensitivity of the farming system, and the adaptive capacity of households (Smit & Wandel, 2006). Enhancing resilience involves not only adopting technical measures but also strengthening social networks, institutions, and market linkages that support adaptive decision-making (Adger, 2006). Understanding farmers' perceptions of climate change is crucial because perception shapes behavior: farmers who recognize long-term changes in temperature and rainfall are more likely to adopt adaptive measures than those who perceive climate variability as random or cyclical (Ezeh et al., 2022).

1. CLIMATE CHANGE IN NIGERIA AND OYO STATE

Nigeria is not insulated from these challenges. The country has recorded increasing climatic variability in the past three decades, with northern regions experiencing desertification and drought, and southern regions facing flooding, soil erosion, and irregular rainfall patterns (Apata et al., 2009; Ayinde et al., 2010). The direct implication is reduced crop productivity, particularly for cereals like maize, which are highly sensitive to water availability and temperature. In Oyo State, situated in the southwest agro-ecological zone, rainfall has historically supported bimodal cropping seasons. However, farmers now report delayed onset of rains, shorter wet seasons, and prolonged dry spells, all of which undermine maize production (Oyekale, 2014). Rising temperatures further exacerbate evapotranspiration, reduce soil fertility, and promote pest and disease proliferation. These local manifestations of climate change present significant risks to maize farmers, whose livelihoods are tied closely to agricultural outputs.

2. FARMERS' ADAPTATION TO CLIMATE CHANGE

Adaptation has emerged as a key strategy for reducing vulnerability and ensuring resilience to climate change in agriculture. Adaptation strategies may be technological (e.g., irrigation, improved seed varieties), behavioral (e.g., adjusting planting dates), or institutional (e.g., policy interventions, extension services). Across SSA, common adaptation measures include crop diversification, mixed farming, soil and water conservation, fertilizer use, agroforestry, and adoption of drought-tolerant crop varieties (Maddison, 2007; Nhemachena & Hassan, 2007).

In Nigeria, empirical evidence suggests that farmers adopt multiple strategies to mitigate climatic risks. Apata et al., (2009) reported that food crop farmers in southwestern Nigeria employ crop diversification, mulching, fertilizer use, and changes in planting time. Similarly, Tambo and Abdoulaye (2013) found that Nigerian farmers increasingly rely on improved maize varieties, mixed cropping, and agroforestry as adaptive responses. Despite these practices, adoption rates remain low relative to the magnitude of climate change impacts. In particular, artificial irrigation remains grossly underutilized, with the majority of farmers relying on rain-fed systems (Abidoye et al., 2017).

3. THE POLICY AND INSTITUTIONAL CONTEXT

At the policy level, Nigeria has made efforts to mainstream climate change adaptation into agricultural development. The National Adaptation Strategy and Plan of Action on Climate Change (NASPA-CCN) emphasizes the need for climate-resilient agricultural practices, while the Federal Ministry of Agriculture and Rural Development (FMARD, 2018) promotes climate-smart agriculture. Despite these frameworks, implementation gaps remain evident, particularly at the grassroots level where farmers often lack the resources and institutional support necessary to translate policy into practice. Oyo State farmers, for instance, frequently highlight the inadequacy of extension services, limited financial support, and insufficient infrastructural development as major barriers to effective adaptation (Ayinde et al., 2010).

4. RATIONALE FOR THE STUDY

Given the centrality of maize to food security and the evident threats posed by climate change, it is imperative to investigate how farmers in Oyo State perceive climate change, the adaptation strategies they employ, and the socioeconomic and institutional factors shaping their production potentials. While numerous studies have analyzed climate change adaptation in Nigeria, many focus on general food crops, regional overviews, or national-scale assessments (Apata et al., 2009; Deressa et al., 2011). Few have examined the specific case of maize farmers in Oyo State, despite the crop's strategic importance.

This study seeks to fill that gap by providing empirical insights into how climate change affects maize production potentials, the adaptation measures adopted, and the constraints limiting effective responses. Such analysis is critical not only for advancing academic knowledge but also for informing policy interventions tailored to local realities. The findings will help guide policymakers, development partners, and extension agencies in designing targeted interventions to strengthen resilience, promote climate-smart agriculture, and ensure sustainable food systems.

This study, therefore, seeks to contribute to the growing body of literature on climate change and agricultural adaptation in Nigeria by focusing on maize farmers in Oyo State. Specifically, it aims to:

- Examine the farm-specific and socio-economic characteristics of maize farmers in Oyo State.
- Assess farmers' perceptions of climate change and their adaptation strategies.
- Analyze the factors affecting maize farmers' production potentials in the study area.
- Provide policy recommendations to enhance adaptive capacity and resilience among maize farmers.

By addressing these objectives, the study will provide insights into the determinants of adaptation behavior among maize farmers and identify entry points for policy and program interventions to enhance resilience and productivity in the face of climate change.

5. METHODOLOGY

The study was carried out in Ido local government area (LGA) one of the rural urban city in Ibadan, Oyo State Nigeria. It has an area of 986km2 and a total population of 103,261 using a growth rate of 3.2% from 2006 census with a population density of 116 persons by square kilometer. Its headquarters is in the town of Ido situated along Ibadan-Eruwa road. The people are predominantly Yoruba and blessed with fertile land which is suitable for agriculture and so an agrarian community. The main occupation of the people is farming mainly food and cash crops such as cassava, maize, yam, vegetable, timber, cocoa, oil palm and kola nut mainly on small scales with significant proportion of the farmers engaging in secondary occupation such as hunting, trading, artisan, civil service, food processing among others.

Sampling Techniques

Simple random technique was used to select three (3) villages in Ido Local Government Area, these are Akufo, Omi-Adio and Aba dada based on the availability of the farmers for the study, 25 questionnaires were administered in Akufo, 20 in Omi-Adio and 25 in Abaa dada, making a total of seventy questionnaires administered. The Local Government Area was purposive selected because of its agrarian nature.

Data Collection and Analysis

The data collected were analysed using descriptive statistics such as tables, frequencies, percentage, means and inferential statistics was used to analyze the factors of maize production in the study.

Regression Model Specified:

$$Y= (a+b1X1+ b2X2 + b3X3 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots b8X8 + \mu)$$

Where: Y= Maize Output in Kilogram; X1 = Educational level (dummy); X2 = Belonging to farmers Association; X3 = Labour source (dummy); X4 = Extension agent contact; X5 = Years of farming experience (years); X6= Source of land (dummy); X7= Fertilizer application (Quantity); X8= Credit source (dummy); a= Constant; b= Parameter estimated and μ= Error term.

6. RESULTS AND DISCUSSIONS

Table 1. Farmers Socioeconomic and Farm Specifics(a)

Variables (N=70)	**Frequency**	**Percentage (%)**	**Mean**
Age			
20-30	14	20.0	
31-40	20	28.6	
41-50	18	25.7	
51-60	11	15.7	
60 and above	7	10.0	43
Gender			
Male	25	35.7	
Female	45	64.3	
Non-educated	21	30.0	
Primary	16	22.9	
Secondary	23	32.9	
Tertiary	10	14.3	
Household size			
1-5	39	55.7	
6-10	30	42.9	
11 and above	1	1.4	5.53
Extension agents contact			
Do not have access	44	62.9	
Have access	26	37.1	
Years of farming experience			
1-5	16	22.9	
6-10	26	37.1	
11-20	22	31.4	
21 and above	6	8.6	11
Source of land			
Inherited	24	34.3	
Bought	18	25.7	
Rented	17	24.3	
Gift	6	8.6	
Government	3	4.3	
Communal	2	2.9	
Fertilizer application			
Do not apply	8	11.4	
Applied	62	88.6	

Table 1. Farmers Socioeconomic and Farm Specifics(b)

Variables (N=70)	Frequency	Percentage (%)	Mean
Type of fertilizer used			
Organic	22	31.4	
In organic	40	57.1	
Source of Irrigation			
Artificial irrigation	17	24.3	
Rainfall	53	75.7	
Farm size used (hectares)			
Small scale (0.1-3.0)	65	92.9	
Large scale (4.0-10.0)	5	7.1	
Source of credit			
Commercial bank	9	12.9	
Agricultural bank	8	11.4	
Cooperative society	14	20.0	
Money lenders	19	27.1	
Friends and family	13	18.6	
Others	7	10.0	
Estimated cost (₦)			
1000-20000	16	22.9	
21000-40000	14	20.0	
41000-60000	13	18.5	
61000-80000	9	12.9	
81000-100000	7	10.0	
100000-200000	7	10.0	
200000 and above	4	5.7	73964
Quantity of maize (tons)			
1-2	6	8.6	
3-4	7	10.0	
5-6	44	62.8	
7 and above	13	18.6	

The result in table 1 shows the farmers socioeconomic and farm specific in the study area.

The age distribution reveals that 54.3% ware within the ages of 31-50years, while 10% are within 60 years and above with mean age of 43 years. The mean age of 43 years indicates that most respondents are in their productive and economically active years, capable of adopting new technologies and practices to mitigate climate change effects.

This is in line with the findings of Salawu (2001) and Oyewo et al., (2014) who noted that the most productive age in agriculture and forestry activities fall within the age group of 31-50 years in Nigeria. The gender distribution of respondents shows that majority (64.3%) ware female while 35.4% are male, This indicating that female engages in maize production than male in the study, underscoring the pivotal role of women in maize production in Oyo State. This is in line with findings of Kang, (2007) which stated that gender plays a vital role in farming practices, also conform with the work of Mgbada (2000), Rahman and Usman (2004), which noted that rural women contribute two-third of the labour force spent in agricultural production and marketing by producing up to 60-80% of food and other products in Nigeria and Africa at large. Thomas and Adebayo (2003), also claimed that majority of rural women took active part in agricultural production. 30.0% had no formal education, 32.9% of the farmers had secondary education, while 14.3% had tertiary education. This implies that higher proportion of the respondents had secondary education and majority had one form of formal education. This conforms to Shehu et al., (2017) and Oke et al., (2022). This could have a positive effect on their awareness of climate change; more than half (55.7%) of the farmers had 1 to 5 members household size. The result further revealed that 37.1% of the farmer had contact with extension agents, 37.1% of the farmers had 6-10 years of farming experience, 31.4% had 11-20 years while 8.6% had above 21years of farming experience with (11) mean years of farming experience, 34.3% of the farmers inherited their farm land while 2.9% source of farmland was trough communal, majority (88.6%) of the farmers applied fertilizer while 11.4% do not use fertilizer due to their inability to afford to buy it or due to the nature of their farm. However, 57.1% of them used in organic fertilizer while 31.5% used organic fertilizer, 97.2% had farm size between 0.1-4.99 hectares which connote small scale farming, 1.4% had between 5-9.99 hectares farm size (medium scale farming), while 1.4% of the farmers had farm size between 10.0 hectares and above (large scale farming). This shows that almost all of the farmer operate in a small scale size of farming system, this in line with the findings of Oyewo et al., (2018) that majority of cassava farmers operate on a small scale farming system. 27.1% of the farmers source their credit through money lenders, 20.0% through cooperative society.

The table also shows that 22.9% of the farmers incurred between ₦1000-₦20,000 per planting season, 20.0% spent between ₦21,000- ₦40,000 while 5.7% spent between ₦201,000- ₦400,000 on their farm per planting season, 62.8% of the farmers harvested between 5-6 tons', 10.0% harvested between 3.0-4.0 tons while1 8.6% of them harvested 7 tons and above in maize produced per season. However, the decision to adopt adaptation measures is shaped by various socioeconomic and institutional factors. Education enhances farmers' understanding of climate risks and available adaptation options (Deressa et al., 2011). Farming experience improves knowledge of indigenous practices and local coping mechanisms (Below et al., 2012). Access to extension services facilitates information dissemination and increases the likelihood of adopting improved practices. Likewise, access to credit empowers farmers to invest in inputs such as fertilizers, irrigation equipment, and improved seeds (Egbetokun & Omonona, 2012).

Table 2. Farmers perception of climate change

Variables (N=70)	Frequency	Percentage (%)
Increased temperature	60	85.8
Decreased temperature	20	28.6
Altered temperature change	14	20.0
No change in temperature	12	17.1
Increased rainfall	30	42.9
Decreased rainfall	60	85.8
Change in timing of rains	23	32.9
Change in frequency of drought	24	34.3
No change in rainfall	11	15.7

Table 2 shows the perception of climate change on the cultivation of maize by the farmers. This is a multiple responses where farmers are given the option to choose more than one responses. The table shows that 85.8% of the farmers experience increased temperature and decreased rainfall, 34.3% experienced decreased rainfall and change in frequency of drought, 32.9% experienced change in timing of rains while 28.6% of farmers experience decrease temperature, it was also revealed that 20.0% of the farmers experienced altered temperature change.

It was further realized that 17.1% of the farmers said that there is no change in temperature, while (15.7%) of farmers in the study perceived no change in rainfall pattern. This finding was in line with the work of Apata et al., (2009). who reported similar perceptions among arable food crop farmers in Southwestern Nigeria. The high level of awareness presents an opportunity for scaling up adaptation strategies since perception is a prerequisite for behavioral change.

Table 3. Farmers Adaptation strategies to climate change

Variables (N=70)	Frequency	Percentage	Ranking
Planting different crops	59	84.3	1st
Planting different crop varieties	58	82.9	2nd
Mixed farming	50	71.4	3rd
Ridges across the slope	41	58.6	4th
Cereal/ legumes intercropping	39	55.7	5th
Shifting cultivation	38	54.3	6th
Planting trees	34	48.6	7th
Use of organic fertilizers	31	44.3	8th
Zero tillage	28	40.0	9th
Irrigation	28	40.0	10th
Use of agricultural insurance	22	31.4	11th

Table 3 shows the adaptation strategies to climate change by farmers in the study area. This is in multiple responses, 84.3% of the farmers adopted the practices of planting of different crops on their farmland which ranked 1st, 82.9% plant different crop varieties (ranked 2nd) as a means of adaptation strategies, 71.4% of the respondents practices mixed farming (ranked 3rd), 58.6% involve in making of ridges across the slope (4th). 55.7% engage in cereal/legumes inter-cropping (5th), 54.3% practices shifting cultivation (6th), 48.6% of them planted trees (7th). Also 44.3% of the farmers use organic fertilizers while 40.0% of the farmers practice irrigation and zero tillage. 31.4% uses agricultural insurance as their source of credit. This is an indication that every of the respondents adopt one or more adoptive measure to climate change in the study area. This is in line with Coster (2015) which stated that every farmer makes use of one or more adoptive strategies as a means of adaptation strategies to climate change in his study.

Table 4. Determinants of maize farmers production potentials in the study area

Variables	Beta	Std Error	T-value	Significant
(Constant)	42.996	7.282	5.905	0.000
X_1 Edu level	-2.029**	1.124	-1.805	0.076
X_2 Association	-1.979	2.490	-0.795	0.430
X_3 Labour source	0.039	1.557	0.025	0.980
X_4 Ext Agent	8.188***	2.708	3.024	0.004
X_5 Yrs of farming	0.973***	0.176	5.540	0.000
X_6 Land source	-0.923	0.925	-0.998	0.322
X_7 Fertilizer app	-6.436**	3.015	-2.135	0.037
X_8 Credit source	0.071	0.870	0.081	0.935
X_9 Climatic condition	-0.258***	0.043	6.000	0.000
R^2	0.56			

Regression table 4 revealed that access/contact with extension agent and years of farming experience were significant ($p<0.01$) and has positive relationship with maize output, the positive coefficient of years of farming experience and access to extension agent will bring about increase in the maize output, or achieve higher productivity, this corroborate the finding of Oke et al., (2022), farmers level of education and fertilizer application has negative coefficient and significant ($p<0.05$) to the maize output, this is not in line with apriori expectation. This therefore implies that farmer level of education and fertilizer application tends to decrease maize output; this may be as a result of low level of education, low level of adoption of modern technologies and farmers' awareness on means of mitigating climate change trough the application of fertilizer at the appropriate time and given quantity or due to low quality or inappropriate timing/dosage of fertilizer application or the possibility that more educated farmers engage in non-farm activities, reducing time and attention devoted to farming. Climatic conditions ($\beta = -0.258$, $p < 0.01$) also negatively affected output, reflecting the detrimental effects of irregular rainfall and high temperatures on maize yields. This may be due to the untimely raining and high level of temperature during the farming season. The model's R^2 of 0.52 indicates that the specified variables explained 52% of the variation in maize output. This moderate explanatory power underscores the multifactorial nature of agricultural productivity, where unobserved variables such as soil fertility, pest incidence, and access to mechanization may also play roles.

It was therefore concluded that educational level, extension agent contact, years of farming experience, fertilizer application and climatic conditions were the major variables influencing maize production in the study area which also correspond to the report of (Mani et al., 2022) that farming experience were among the factors affecting crop production.

CONCLUSIONS

The research however concluded that less than half of the farmers used hired labour, and do not use organic fertilizer, majority of the farmers were aware of climate change, adopt planting of different crops and varieties, practices zero tillage and mixed farming as means of climate change adaptation strategies. However, adoption of artificial irrigation and modern farming methods is still very low in the study area, leading to low maize outputs. These findings showed that young people are better placed in adoption of new technologies than older people. It was also find out that farmers levels of education, extension agent contact, years of farming experience and fertilizer application were the major variable influencing maize output and Lack of credit facilities, lack of vital information and data regarding climate among others were the major constraint to the adoption of climate change and coping strategies by farmers in the study area.

Policy Recommendations

Based on the findings, the following recommendations are offered:

- Strengthen Extension Services: Government and development agencies should improve the frequency and quality of extension visits to disseminate climate-smart agricultural practices and new technologies.
- Facilitate Access to Credit: Affordable and timely credit should be made available through cooperatives, microfinance, and agricultural banks to enable farmers to invest in irrigation, improved seeds, and fertilizers.
- Promote Climate-Smart Inputs: Encourage the use of organo-mineral fertilizers and bio fertilizers instead of synthetic fertilizers to improve soil health and reduce environmental harm.

- Enhance Irrigation Infrastructure: Invest in small-scale irrigation systems and water harvesting technologies to reduce dependence on erratic rainfall.
- Encourage Diversified Livelihoods: Support farmers with training and inputs for mixed farming and intercropping to spread production risks.
- Improve Agricultural Insurance: Design affordable insurance schemes to protect farmers against crop losses due to climate shocks.
- Research and Development: Strengthen linkages between research institutions and farmers to ensure timely dissemination of innovations and locally adapted climate-resilient maize varieties.

Implementing these recommendations will not only improve maize farmers' productivity but also contribute to national food security, poverty reduction, and the achievement of Sustainable Development Goals (SDGs) 1 (No Poverty), 2 (Zero Hunger), and 13 (Climate Action). Future studies should explore long-term impacts of specific adaptation strategies and the role of institutional support systems in enhancing farmers' resilience to climate change.

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CHAPTER 2
DRY SPELL LENGTH ANALYSIS FOR CROP PRODUCTION USING MARKOV-CHAIN MODEL IN BENIN: CASE OF SYNOPTIC STATIONS IN BENIN

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INTRODUCTION

In the current context of climate change, even if the entire scientific community agrees on the reality of a climate change and on future global warming, it still sometimes remains to distinguish between a real change and the natural climate variability. Precipitation is the oldest and most commonly recorded climate variable. For these reasons, they are a valuable indicator for studying climate change.

Indeed, there are extreme dry events that occur even within the rainy seasons and that it is still too early to reduce to climate change, and it is more prudent at the present time to consider them as interannual climate variability. The observation of dry days in climatic zones is growing steadily. While most authors agree in recognizing the potential role of climate in environmental degradation phenomena, the climate trend is not always easily perceived and remains controversial.

The drought observed since 1970 in West Africa and particularly in Benin has less severe and less damaging consequences in more equatorial regions such as Benin [3]. The drop in rainfall is a strong and obvious signal to the gradual onset of drought in a coastal country like Benin [4] and it is important to analyze the dry sequences within the rainy season with a view to understand their trend. Climate change issues have been at the center of the concerns of scientists and political decision-makers around the world for several years.

The great importance attached to climate change results from its immediate consequences on the hydrological cycle, the environment and socio-economic activities. Among the large-scale climatic events, we note the drought that has affected the two tropical bands of our planet. Located in West Africa, Benin is one of the countries concerned.

The most dominant economic activities in rural areas of Benin are agriculture, animal husbandry and fishing. However, it is obvious that these activities require water control during the rainy season for their sustainability. It is currently observed that days without rain are more frequent in the rainy season.

These rainless days during the rainy seasons could negatively impact rain-fed agriculture which occupies the majority of the rural population of Benin.

A good knowledge of these days without rain can make it possible to take the appropriate measures to limit the negative impacts on agricultural production. The main cereal crop grown in the study area is mainly maize. Maize occupies a few small areas of the farming areas available to farmers in Benin. Maize is a crop with higher water requirements than millet and sorghum. He is possibly more feverish in the face of dry spells lasting 4 days with a risk of water stress. But it must be recognized that this is when speculation is heading and vulnerable to dry spells because it is the most restrictive phase of the growing cycle in terms of water requirements. The occurrence of dry or rainy episodes at certain key stages of the rainy season adversely affects the development of crop plants, which can prevent the plant from completing its entire vegetative cycle (Hachigonta, 2006. Significant dry sequences for each crop are factors that reduce agricultural yield.

The general objective of this study is to search for a breaking trend in the series of dry sequences over the period from 1970 to 2018 using rainfall data from synoptic stations in Benin.

The specific objectives are broken down into three objectives, namely:

- Analyze of dry spells with the Markov chain probability model
- and its implications on crop production in Benin, so as to minimize unexpected damage due to long dry spells;

In order to understand the change (variability) of the dry sequences of the regions of Benin and its impact on the environment and agriculture in Benin. This study of these climatic and agro-climatic parameters and the preparation of climate information constitutes an action within the framework of adaptation to the phenomena of climate change and possibly the improvement of agricultural yields with a view to food security.

1. MATERIAL AND METHODS

The data used in this work consist of daily rainfall readings from six synoptics stations in Benin. The data was made available by the Agence-Météo Bénin and (Agence pour la Sécurité de la Navigation Aérienne) ASECNA. The study variable is the length of consecutive dry days or dry sequences from the period 1970 to 2018. The positions selected obey criteria of continuity, duration of the information available and data quality.

The choice of stations was also made in such a way as to allow the most homogeneous possible coverage of the study climatic zone. The choice of the period 1970 to 2018 depends on the availability of data because there is generally a gap for most stations towards the end of the years 1952 which introduces a bias in the calculation of the statistical tests. In addition, it is with a view to analyzing the trend of dry sequences after the drought of 1970, the consequences of which are very worrying in the West African zone.

In order to search for trends in dry sequences, we extracted the dry sequence length per year and decade with Matlab programming software.The REMO model data to 2025 at 2100 of climate change project from the six synoptics stations in Benin is using to detect the dry sequence length per year and decade.

Table 1. Presentation of rainfall stations [data from asecna Benin]

Station	Longitude	latitude	Altitude (m)
Kandi	2°56’	11°08’	290
Natitingou	1°23’	10°19’	460
Parakou	2°36’	9°21’	392
Save	2°28’	8°20’	199
Bohicon	2°04’	7°10’	166
Cotonou	2°23’	6°21’	4

Figure 1 gives us a geographical overview of the measurement sites in Benin and Africa.

Figure 1. Geographical location of synoptic stations in Benin and their location in Africa

Materials Used

Two essential softwares were used to analyze climatological phenomena. These are Matlab and the R software. Matlab software has been used for data processing. To study the link between the maize yield in each agricultural region and the dry sequences we used the R software.

1.1 Methods

A rainy event j in a wet season i will be characterized by its duration Di, j, symbolizing the number of rainy days and by the total height of accumulated rain h i, j in di, j rainy days, in mm:

$$\text{Hi,j}=\sum_{k=1}^{Di,j}(\text{hi}) \qquad (1)$$

Where hi represents the total daily rainfall in mm with h i> 0. To define the chronological position of a rainy event within the season of rains, we use an additional parameter which is the weather. In this contribution, the time between the end of a rain event and the start of the next rain event is the dry event or dry sequence Zij representing the number of days without rain between two consecutive rain events.

If Zij is assigned to the last event preceding the dry season, we have, Z ij = 0 for the last event of a season (j = Ni). The number of dry events per season is therefore N i - 1. The length of the dry sequences Li is defined as the duration between the start of the first and the end of the last rainfall event of a given season, while the length of the hydrological year Ais determined by the interval of time between the beginning of two subsequent wet seasons.

$$L_i=\sum_{j=1}^{Ni-1}(Zij) \qquad (2)$$

Where Li is the number of dry days or the length of dry stretches in days and Ni is the number of events in season j. To respond to our concern, we counted the maximum length of the dry sequences per year, then the average of the maximums over the period 1970 to 2009. The extracted parameters are shown in Figure 2.

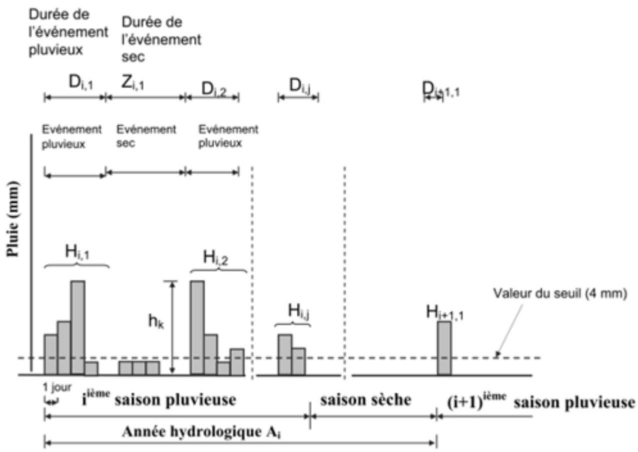

Figure 2. Representation of the parameters extracted by event [14]

1.2 The Markov Chain Probability Model

The Markov chain probability model for the analysis of wet and dry periods was first introduced by Gabriel and Neumann (1957) using 27 years (1923-1950) rainfall data from November to April in Tel Aviv, Israel, considering the threshold of 0.1 mm (Gabriel and Neumann, 1957) [8].The results were validated with chi square tests. Since then, Markov's process models have been widely used by many authors around the world. Therefore, this study aims to analyze the length of the maximum dry sequences and its implications for the cultivation and yield of maize in Benin, so as to minimize unexpected damage due to long periods of drought and to have effective planning for agriculture.

The Markov chain method was applied to determine the persistence of drought on a daily scale. Indeed, given any day given dry data or not and preceded by a dry day or not, one may wonder what is the probability of having a dry day the following day or a wet day. The process expresses conditional probabilities of changing from the previous day's state to the current day's state. Thus the state of day t depends only on the state t-1 for the Markov process of order 1. Eventually, it will depend on the states t-1 and t-2 for the Markov process of order 2 and the same logic is followed for the higher orders.

The justification for the use of the Markov chain in this case is explained by the fact that the feedbacks of the earth-atmosphere system make it possible to admit that each new realization of an event at time t depends on previous realizations (Afouda., et al., 1997) [9]. It is therefore one statistical tool among many that makes it possible to calculate the probability of occurrence of an event at a given moment, knowing that it occurred the moment before. The determination of the probabilities of advent leads to consider precipitation as stochastic processes occurring randomly [12]. The establishment of a statistical model is necessary for the application of Markov chains: It is defined according to the following relations:

- Consider a sequence of n consecutive days:
  Let be xi(i=1,2,3,4..) a series n random variables taking the values
  xi = d(dry) and xi= w(wet) . So for example x2=d means that the second day of the sequence is dry and x5=w means that the 5th day is wet.
- Let be x_i (i=1,2,3,4..) a series n random variables taking the values x_i = d (dry) and the probability that the sequence (x1,x2, x3, x4… xn) is realized that is to say thatP(x1) is the probability that the event of day n-1 of the sequence will occur and so on up to order n.
- The application of the Markov property to order 2 leads to the following writing:

$$P(x1,x2,\ldots,xn)= P(x1)\times P(x2/x1) \times P(x3/x2,x1) \times\ldots\times p(xn/xn-2,xn-1) \quad (3)$$

This equation is used to calculate the different probabilities of combinations contained in the sequence. Thus, to determine the state (rainy or dry) of a given day we will refer to the state of the two previous days. At order 3, logically the state of the previous three days will make it possible to predict the state of the day in question.

The 2nd order Markov chain will require the determination of the number of dry sequences of length greater than or equal to two days. As announced above, a dry sequence is automatically a time without precipitation or even with precipitation not reaching the threshold set for the study. The scoring will be adopted in the rest of the reasoning of the study:

- (wd) defined as a dry day preceded by a rainy day and its probability will be noted Pwd

Thus the expression which will allow us to have the probability of having two dry days surrounded by rain is as follows:

$$Pwddw = P(d/\ dw) \times P(w/\ dd) \qquad (4)$$

P(d/dw) : the probability of having a dry day knowing that the day before it was dry and the day before wet;P(w/dd): The probability of having a rainy day knowing that the two days beforewere dry.It will be noted

$$q2 \text{ and } q2 = P(d/dw) \times P(w/dd) \qquad (5)$$

The probabilities of having 3 days and 4 dry days framed by rain are respectively q3 and q4 are given by the following expressions:

$$q3=Pwdd=P(d/dw)\times P(d/dd)\times P(w/dd)=PwddxPdddx\ Pddw \ (6)$$

$$q4=Pwdddw=P(d/dw)\times P(d/dd)\times P(d/dd)\times P(w/dd)=Pwdd\times P2ddd\times Pddw \ (7)$$

When we generalize, considering for n dry days, we obtain:

- For Markov chains of the 2nd order, the probability that a dry sequence lasts n day is given by the relation qn

$$q_n=(1-P_{wdw})(1-P_{wddw})^{n-2}(P_{wddw}) \quad (8)$$

- For Markov chains in order 3:

$$q_n=(1-P_{wddw})(1-P_{wdddw})^{n-3}(P_{wdddw})(9)$$

The different probabilities contained in the expression of the Markov chains of the second and 3rd order are calculated empirically:

$$P_{wdw}=\frac{Number\ of\ sequence\ wdw}{Number\ of\ sequence\ wd....} \qquad (10)$$

$$P_{wddw}=\frac{Number\ of\ sequence\ wddw}{Number\ of\ sequence\ wdd....} \qquad (11)$$

$$P_{wdddw}=\frac{Number\ of\ sequence\ wddw}{Number\ of\ sequence\ wddd....} \qquad (12)$$

The probability that a dry sequence lasts n days is given by:

$$q_n=\frac{number\ of n\ dry\ spell}{\sum_{i=1}^{30} Nunberof\ wd......dw} \qquad (13)$$

- The distribution of the time remaining until the next defined dry sequence by the process is the same regardless of the time already spent in the initial state.

The only continuous random variable distribution having this property is the exponential distribution. This result allows us to describe a continuous-time Markov chain in an equivalent way as follows:

$$P(Ti \leq t)=1\text{-}e\text{-}qn\ ;\forall t>0 \qquad (14)$$

The mathematical expectation is:

$$E[Ti]=1/qn \qquad (15)$$

The approach consisted of identifying the dry sequences according to the criteria established above and performing the various calculations to highlight the probability distributions by station and agricultural area.

1.3 Critical Dry Period

Through the historical series of dry sequences formed, we extracted the stations that recorded dry sequences of more than 15 days during the period 1970-2018. Then we determined the critical time of decadal satisfaction of the water needs of the but during the rainy season where the dry period was observed as well as for the decade that follows it.

The critical duration of the dry period is the period of time that the ecosystem can fill. It is the ratio between the available soil moisture and the vegetation transpiration rate.

If the transpiration demand is greater than the amount of soil available humidity, the development of the plant will be hampered or, in the worst case, the plant will wilt.

The length T (days) of the critical dry period can therefore be calculated at each point in space as the ratio between the available soil moisture RFU (mm) and the potential evaporation ETm (mm day $^{-1}$):

$$T=\frac{RFU(mm)}{ETm(\frac{mm}{day})} \qquad (16)$$

The corresponds to the raw water requirements since it is considered that there is no water input, the available water will be just the RFU of the soil.

Having only the daily water requirements and the available water reserve, we calculate the time during which the plant will be able to benefit from the water by calculating the ratio between the RFU and the daily water with

$$ETm(mm/day)=Kc\times ETP \qquad (17)$$

ETm: (mm per day) is the maximum crop water requirement,
Kc: crop coefficient;
ETP: (mm per day) the potential evapotranspiration and

$$RFU\ (mm)=p\times RU(mm)=p\times Zr(m)\times RU(mm/m) \qquad (18)$$

RFU: the available water reserve,
P: drying factor
Zr: root depth (m)
RU: the available soil moisture (mm)

2. RESULTS

The spatio-temporal variability of intra-seasonal of dry sequences by each station are looking like that :

Parakou's Station

The crop coefficient (kc) and root depth for water balance calculations were applied to a 120 days variety of maize (Table 2), which corresponds to crop varieties commonly used by farmers in Benin.

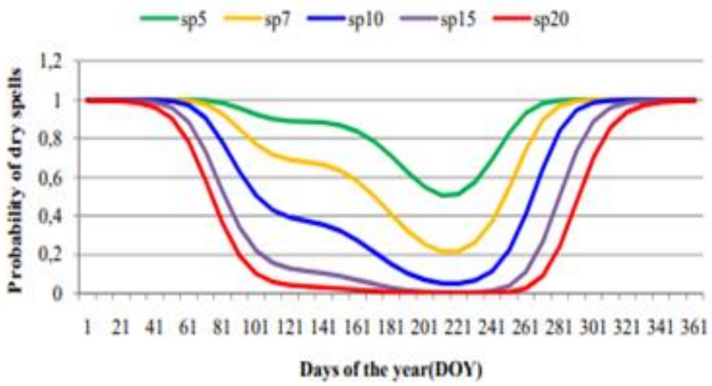

Figure 3. Markov-Chain gtmodel output of dry spells for Parakou

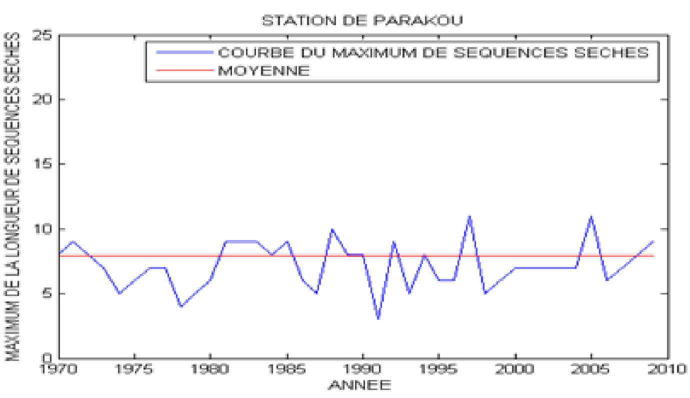

Figure 4. Annual maxima dry spell distribution of Parakou for the period 1970-2010

Natıtıngou Station

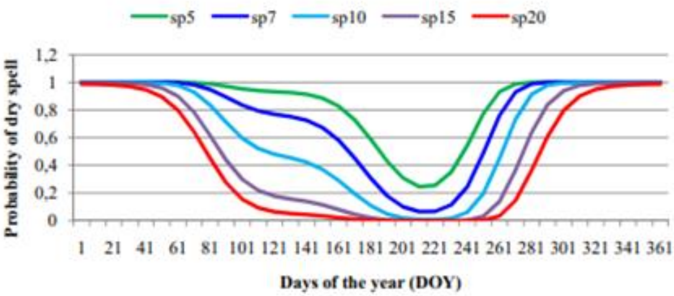

Figure 5. Markov-Chain model output of dry spells for Natitingou

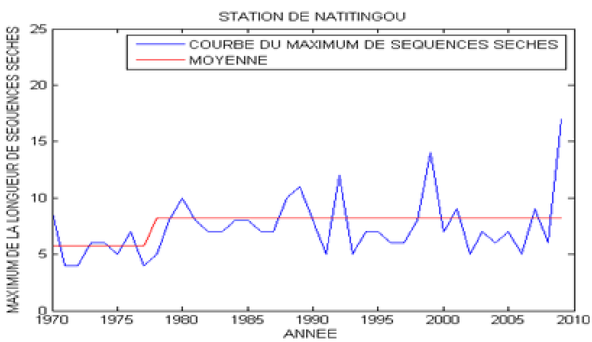

Figure 6. Annual maxima dry spell distribution of Natitingou for the period 1970-201

Bohicon's Station

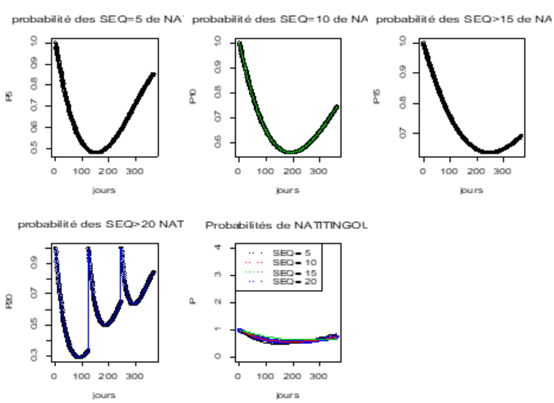

Figure 7. Markov-Chain model output of dry spells for Bohicon

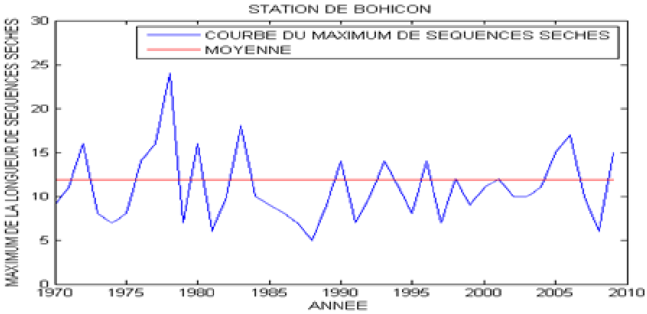

Figure 8. Annual maxima dry spell distribution of Bohicon for the period 1970-2010

Cotonou's Station

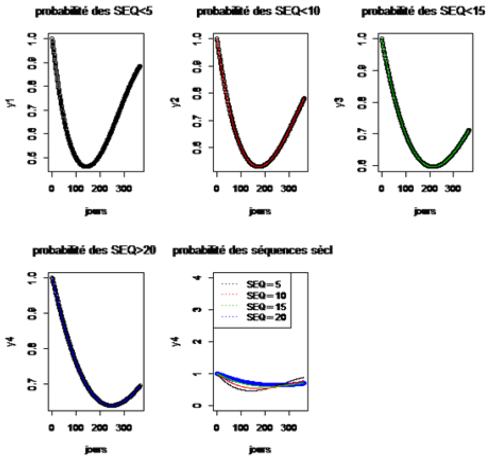

Figure 9. Markov-Chain model output of dry spells for Cotonou

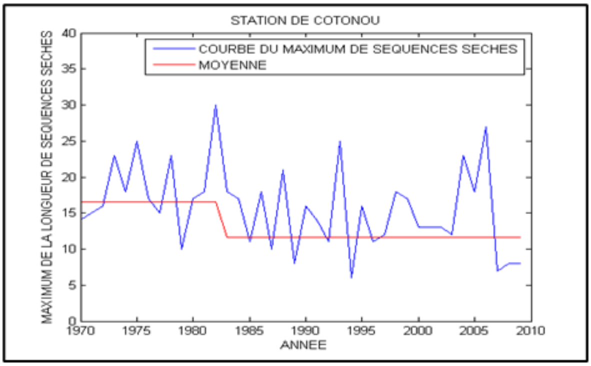

Figure 10. Annual maxima dry spell distribution of Cotonou for the period 1970-2010

Save's Station

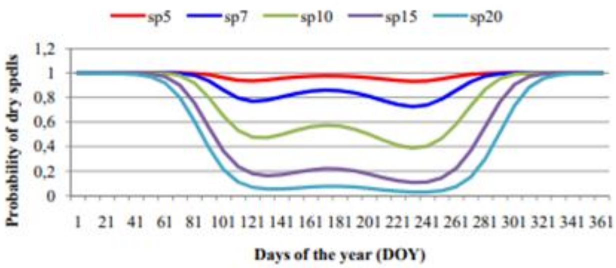

Figure 11. Markov-Chain model output of dry spells for Save

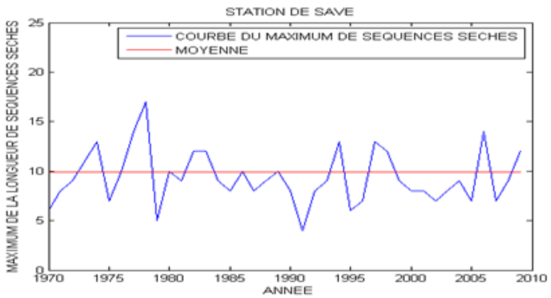

Figure 12. Annual maxima dry spell distribution of Save for the period 1970-2010

According to Barron [13], Markov model is able to analyze the agricultural dry spell lengths and respective risks. He reported that the probabilities of agricultural dry spell exceeding 10 days in East Africa varied from 20% to 90% or more depending on onset of rainy season. In general, this implies that growing crops in the area was under high probability of risks, given the harsh climatic condition, very high rainfall variability in this area and food aids were given almost every year over the past three decades.

2.1 Impact of Dry Sequences on Cereal Crops (Maize)

The Table 2 indicates that on sandy soils, the duration of the water stock is low and that after 4 days the RFU is completely exhausted. From this same table, we can conclude that a dry sequence of more than 4 days constitutes a risk of lower yields of maize especially during the heading phase where it could reach the wilting point.

Table 2. Calculation of the number of significant dry days for corn (In north of Benin)(a)

	May			**Jun**			**Jully**			**August**		
Decade	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Mean ETP (1970-2018)	63	67	72	58	59	54	49	49	50	41	44	50
Kc	1	1	1	1	1	1	1	1	1	1	1	1
Zr(m)	1	1	1	1	1	1	1	1	1	1	1	1
ETM (mm)	72	77	83	66	68	63	56	56	58	48	51	57
RU (mm/m)	55	55	55	55	55	55	55	55	55	55	55	55
RU (mm)	66	66	66	66	66	66	66	66	66	66	66	66
p	0.5	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.5
RFU (mm)	33	30	30	33	33	37	36	36	36	40	40	36
ETM (mm/day)	7	8	8	7	7	6	6	6	6	5	5	6
T (days)	5	4	4	5	5	6	6	6	6	8	8	6

Table 3. Calculation of the number of significant dry days for corn (In north of Benin)(b)

	September			**October**			**November**			**December**		
Decade	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Mean ETP (1970-2018)	43	50	54	58	59	54	49	49	50	41	44	50
Kc	1	1	1	1	1	1	1	1	1	1	1	1
Zr(m)	1	1	1	1	1	1	1	1	1	1	1	1
ETM (mm)	49	57	62	66	68	63	56	56	58	48	51	57
RU (mm/m)	55	55	55	55	55	55	55	55	55	55	55	55
RU (mm)	66	66	66	66	66	66	66	66	66	66	66	66
p	0.6	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6
RFU (mm)	40	36	36	33	33	36	36	36	36	40	40	36
ETM (mm/day)	5	6	6	7	7	6	6	6	6	5	5	6
T (days)	8	6	6	5	5	6	6	6	6	8	8	6

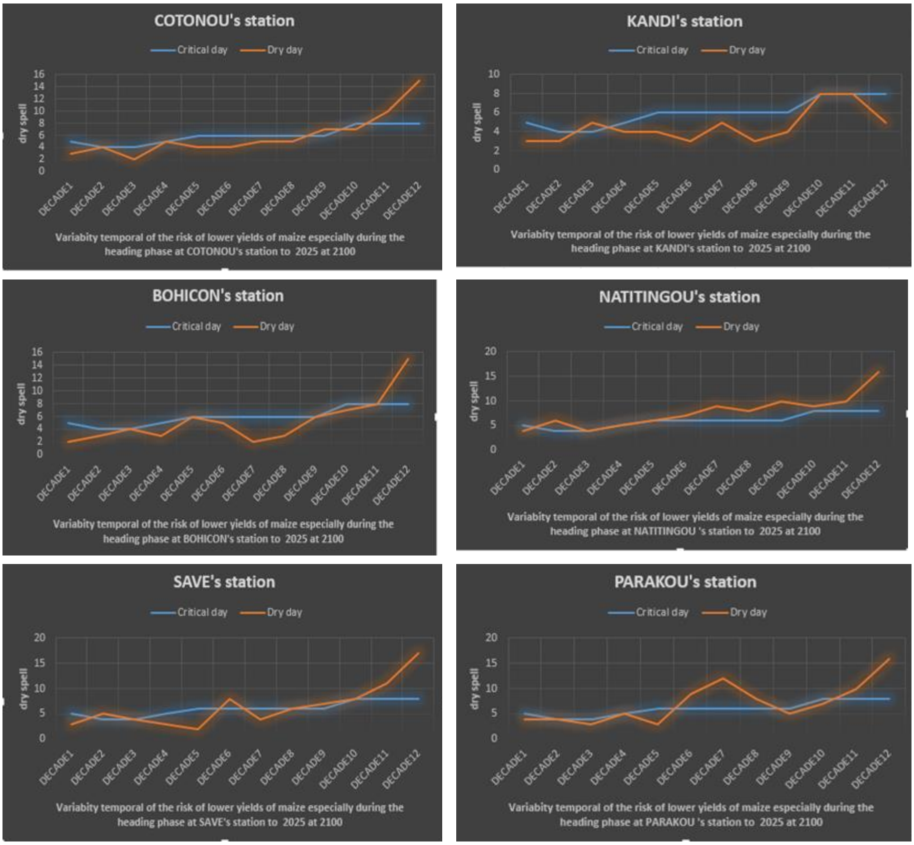

Figure 8. Variabity temporal of the risk of lower yields of maize especially during the heading phase at synoptic's station to 2025 at 2100

3. DISCUSSION

The results of the study revealed that dry spell lengths of the considered days: (seq5) 5 days, (seq 10) 10 days, (seq 15) 15 days and (seq 20) 20 days varies from place to place over the study areas of Parakou, Save, Natitigou, Bohicon, and Cotonou. In line with this, the impacts caused due to the dry spell lengths also varies. Even during themain rainy season of Benin: June, July, August and September (MJJA), the probability of dry spell length of 5 days was about 90% in the south of Benin. The probability of dry spell length of two weeks was also more than 20%. On the other hand, the probability of dry spell length of 20 days was below 20%.

On the other hand, in Cotonou, Bohicon, Save stations the probability of dry spell length of 5 days was found to be 85% during 181 days of the year (1st decade of June), then it declined to below 50 % by 221 day of the year (3rd decade of July). Beginning from 223 days of the year, the probability that the area faced dry spell length of 5 days had been increased up to 100% by 301 days of the year (3rd decade of September). It hasbeen also clarified that in parakou's and natitingou's station, the probability of dry spell lengths of 15 days or the two weeks has been reached about 30% in July. However, the probability of the occurrences of 10days, 15 days, and 20 days were fall below 8% during the main rainy season of the areas, JJAS in the north of Benin. This is the critical time for planting crops. Thus, the crops in the area might be influenced due to the high occurrences of the dry spell lengths of 5 days than any other dry spell lengths occurrences.

The impact of its dry events on the development of crops is appreciable depending on the vegetative cycle during which the dry period occurs.

A dry sequence greater than 4 days was considered significant for maize. These long-lasting dry sequences have a fairly low probability of occurrence (<5%). Short-lived dry spells have the highest probability values (> 30%) but are harmless to crops. we can conclude that a dry sequence of more than 4 days constitutes a risk of lower yields of maize especially during the heading phase where it could reach the wilting point.

CONCLUSION

This analysis of the frequency distribution of dry episodes in Benin's synoptic stations shows that short-term dry episodes (< 5 days or between 5 and 10 days) are the most frequent. Prolonged dry sequences (10 to more than 20 days) are almost absent at most of the stations studied and rarely intervene (1 to 2 years out of 15). From the results, we can retain the probability of dry spelllength of 5 days was about 75%. The probability of dry spell length of two weeks was also more than 20%. On the other hand, the probability of dry spell length of 20 days was below 20%maxima of dry sequence length to the station of Bohicon, Savè, Cotonou and Kandi. It hasbeen also clarified that in parakou's and natitingou's station, the probability of dry spell lengths of 15 days or the two weeks has been reached about 30% in July.

However, the probability of the occurrences of 10 days, 15 days, and 20 days were fall below 8%. A dry sequence of more than 4 days constitutes a risk of lower yields of maize especially during the heading phase where it could reach the wilting point. We note a risk of lower yields of maize at KANDI'S station at third decade; to 7th decade at 10th at NATITINGOU'S station; at seconde decade and 6th decade at PARAKOU'S station; to decade 6 at SAVE'S station.

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CHAPTER 3
THE CLIMATE-SMART CROPS FOR A SUSTAINABLE FUTURE

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INTRODUCTION

Sustainable farming practices are of paramount importance in a time when environmental degradation and climate change pose a threat to the world's food supply. With agricultural yields and food supply at risk due to extreme weather, rising temperatures, and changing precipitation patterns, agriculture is under unprecedented pressure to adapt. Amidst these difficulties, millets—small-seeded grasses noted for their adaptation and resilience—have drawn interest as climate-smart crops that provide significant advantages in terms of nutritional content, flexibility, and resilience (Meena et al., 2021).

For thousands of years, millets have been a vital part of traditional farming in dry and semi-arid environments, flourishing when other mainstays like wheat and rice sometimes fail. They are essential for food security in the face of climate variability because of their resistance to drought, short growing season, and capacity to flourish on poor soils (Saleem et al., 2023). Millets have deep root systems that improve soil structure and encourage carbon sequestration, which improves soil health, conserves water, and supports biodiversity. By giving trees shade and ground cover, millets help sequester carbon in agroforestry systems.

Millets are nutrient-dense, high in protein, fibre, vitamins, and minerals that help prevent malnutrition and improve food security, especially in areas where there is a lack of access to food. Consuming them has been associated with health advantages like better digestion, a lower chance of developing chronic illnesses, and an increase in general wellbeing (Amadou, 2011).

Millets also help agricultural diversity and cultural legacy by preserving biodiversity and traditional farming techniques (Amadou, 2011). They are frequently cultivated with techniques that are well suited to the regional climate, which promotes the preservation of native customs and expertise.

1. MILLETS AND IT’S CLASSIFICATION

A diversified group of annual cereal crops from the Poaceae family, millets are small-seeded and tolerant of harsh environmental circumstances. They can survive in poor soils and extremely hot temperatures with little water. Important species include pearl millet, which is used in rotis, porridges, and traditional beers.

It has strong roots, grows to a height of three meters, and is rich in iron, magnesium, zinc, and protein. Finger millet is used in porridges, unleavened bread, and snacks like ragi mudde and ragi dosa. Its small, round grains are high in calcium, iron, phosphorus, and vital amino acids (Anitha et al.,2021).

Proso millet has small, round grains and a short growing season, high in protein, fiber, phosphorus, and magnesium, used in cereals, animal feed, and gluten-free baked goods. Barnyard millet, with rapid growth and high yield in poor soils, is rich in dietary fiber, iron, and protein, ideal for weight management, and used in fasting foods like kheer and pulao. Little millet, adaptable to various soils and brief rainy seasons, is rich in B vitamins, iron, zinc, and antioxidants, used in upma and idli. Kodo millet has long, slender grains, resilient in drought-prone areas, high in dietary fiber, protein, and polyphenols, used in dosa and biryani (Anitha et al., 2021).

2. DISTRIBUTION OF CULTIVATION OF MILLETS

A diverse range of agroclimatic conditions is reflected in the wide geographical distribution of millets, a versatile group of crops. Millets are a historically significant and nutritionally valuable crop that have been farmed on every continent. They are particularly important for ensuring food security in dry and semi-arid countries.

2.1 Global Distribution

Millets are grown all over the world and do well in a variety of environments, from cold, temperate regions to hot, dry deserts. India became the world's biggest producer in 2023, accounting for 15.5 million metric tonnes, or 38.40%, of the world's millet production. The country mostly grows finger, pearl, and foxtail millet (Meena et al., 2021). Following India, Niger accounted for 11.85% of global production, highlighting its reliance on millets as a staple crop for food security.

China continued to be a major producer in Asia, contributing 8.75% of the world's production with a focus on foxtail millet. An important component of West African agriculture, millets are produced in both Nigeria (6.29%) and Mali (5.788%), as shown in Fig. 2. (APEDA, 2024).

With contributions of 5.43% and 3.73%, respectively, Sudan and Ethiopia were also noteworthy producers, demonstrating their importance in promoting agricultural diversity and resilience in the face of climate concerns.

Senegal, Burkina Faso, and Chad each contributed 3.55%, 2.94%, and 2.25% to the world's millet production, highlighting the continent of Africa's extensive millet farming (P et al., 2023). Prominent European producers include Russia and Ukraine, which produce 1.5 million metric tonnes and 1.1 million metric tonnes of proso millet respectively per year (APEDA 2024). It is mostly used as livestock feed and birdseed, but it is also becoming more and more popular for human consumption because of its gluten-free qualities and health advantages. In order to promote agricultural diversification and food security, millet production increased in Brazil as well, contributing about 0.3 million metric tonnes (P et al., 2023).

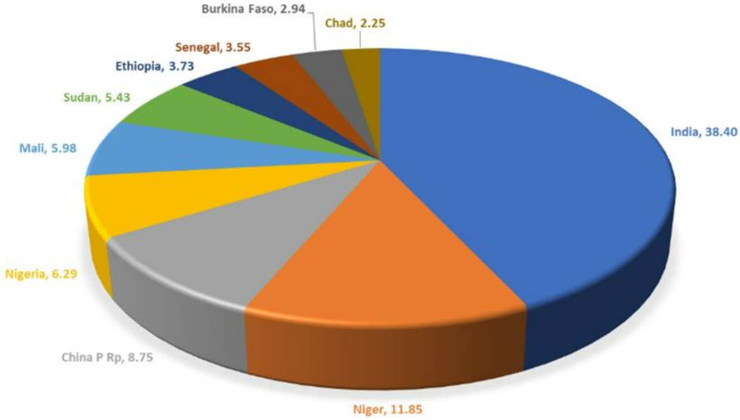

Figure 1. Global distribution of millets 2023-24

2.2 Indian Distribution

As the world's top producer and consumer of millet, India is in a dominant position. Numerous millet species that are suited to regional conditions and culinary customs are grown throughout the nation due to its varied climate zones and cultural diversity. According to Sreekala et al. (2022), Rajasthan accounted for 32% of India's millet production in 2023, with Uttar Pradesh following closely behind with 18%. Karnataka and Maharashtra each supplied 11%, with sorghum and pearl millet being their main crops.

A total of 8% of the country's millet was produced in Haryana, 7% in Madhya Pradesh, and 4% in Tamil Nadu. The combined contributions of Andhra Pradesh, Gujarat, and Uttarakhand to the whole production amounted to 7% (Millet Cultivation in India: History and Trends, 2024) (figure 3). This geographical diversification highlights how widely millet is cultivated in India, where it is extensively incorporated into agricultural techniques and dietary customs, greatly enhancing food security, nutritional diversity, and sustainable farming. Aiming to address malnutrition, climate change, and agricultural sustainability, government initiatives like the National Food Security Mission and the inclusion of millets in public distribution systems have further supported their cultivation and consumption, resulting in a 25% increase in millet production compared to the previous year (Sreekala et al., 2022).

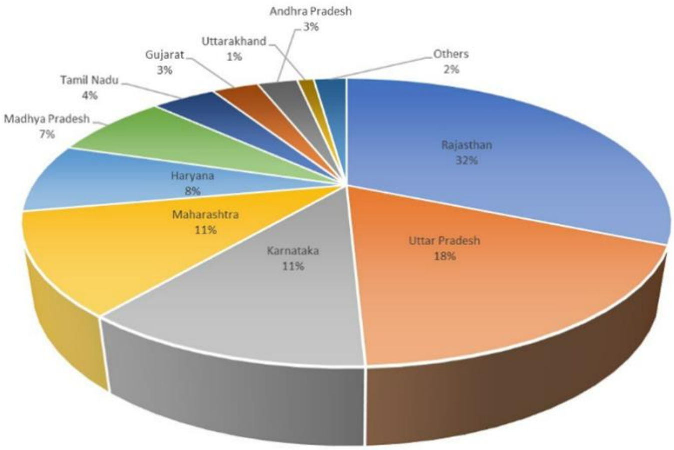

Figure 2. State-wise millet production 2023-24

3. CLIMATE-SMART CHARACTERISTICS OF MILLETS

Due to their innate qualities that make them ideal for sustainable farming methods and climate change adaptation, millets are frequently referred to as "climate-smart" crops. Their potential to meet the issues posed by climate change is highlighted by their ability to thrive in varied agro-ecological settings and their resilience to environmental shocks.

Drought Tolerance

Millets are particularly known for their remarkable drought tolerance, which is one of their climate-smart qualities. In arid and semi-arid areas with scarce water supplies, millet varieties such finger millet, foxtail millet, and pearl millet have developed (Millets: Climate Smart Seeds of the Future, n.d.).

According to data from agricultural studies, pearl millet requires as little as 300–400 mm of yearly rainfall to give good yields, while crops like maize require 600–700 mm (Millets: Climate Smart Seeds of the Future, n.d.). The ability of millets to flourish in low-water situations promotes sustainable water management in agriculture in addition to bolstering food security.

Heat and Temperature Resilience

Millets are resilient to heat stress and temperature extremes because they have adapted to a wide variety of temperature conditions (Bandyopadhyay & Muthamilarasan, 2017). Because of their versatility, they are especially useful in areas where climate change is causing temperatures to rise and frequent heat waves. Given their ability to withstand excessive heat, crops are less likely to fail during times of extreme temperature swings and help stabilise crop production in hot areas.

Short Growing Season

The growing seasons of millets are comparatively shorter than those of other important cereal crops like wheat and rice. Farmers may harvest millets more quickly thanks to their quick growth and maturation cycle, which typically lasts 60 to 90 days (Millets: Climate Smart Seeds of the Future, n.d.). This trait is especially helpful in areas with brief rainy seasons or in systems of multicropping where millets can be planted in between major crops.

Adaptability To Marginal Soils

Millets have remarkable adaptability to marginal soils that have low levels of fertility and nutrients. In light of this quality, they can be grown in degraded areas where other crops might not be able to flourish. The ability of millets to adapt to marginal soils plays a major role in supporting sustainable farming methods.

With their broad root systems, they can increase soil organic matter content and enhance soil structure, all without the need for artificial fertilisers (Bandyopadhyay & Muthamilarasan, 2017). Millets are essential for sustaining agricultural productivity and halting more land degradation in areas with depleted soils.

Biodiversity and Ecological Balance

Different types of millet are commonly planted together or alongside other crops in mixed cropping or intercropping systems. This approach boosts beneficial insect populations, diversifies crops, and manages pests and diseases better (Lenka et al., 2020).

By organically controlling insect populations through crop diversity, millets can be used as an intercrop to lessen the need for chemical pesticides (Millets: Climate Smart Seeds of the Future, n.d.). Millets help create agricultural ecosystems that are more robust and sustainable by promoting biodiversity and ecological balance.

Nutritional Resilience

According to Lenka et al. (2020), millets exhibit nutritional resilience by offering a well-balanced combination of carbs, proteins, dietary fibre, vitamins, minerals, and antioxidants, even in resource-constrained contexts. Due to their high content of vital minerals like iron, magnesium, phosphorus, and B vitamins, they are an excellent dietary source that can help prevent malnutrition and promote food security.

Millets' high dietary fibre content promotes digestive health and aids in the treatment of chronic illnesses including diabetes and cardiovascular disease (Lenka et al., 2020).

4. SOCIAL AND ECONOMIC BENEFITS OF MILLETS

In India, millets are grown and consumed for their many social and economic advantages, which have a big impact on the economy and society as a whole. These grains contribute to economic growth, livelihood creation, cultural preservation, and food security in addition to offering vital nutrients.

Nutritional Security

Millets are extremely nutrient-dense and offer a plethora of health advantages that support nutritional security, particularly in marginalised populations. They provide a well-balanced mix of vital nutrients and are high in dietary fibre, vitamins, minerals, and antioxidants. For example, finger millet has a high calcium content of up to 344 mg per 100 grammes, which is crucial for healthy bones (P et al., 2023b). With iron levels as high as 8 mg per 100 grammes, pearl millet can help prevent anaemia (Ceasar & Maharajan, 2022).

Improving nutritional security and addressing the problem of malnutrition can be accomplished through encouraging the production and consumption of millets. By promoting a varied and well-balanced diet, millets help to lower the incidence of nutrient shortages and enhance general public health. According to a 2023 study conducted by the International Food Policy Research Institute (IFPRI), rural communities' consumption of calcium increased by 25% and iron deficient anaemia cases decreased by 30% when millets were incorporated into their diets.

Food Diversity and Cultural Preservation

Promoting millets is essential to retaining traditional food systems and sustaining cultural diversity. Many Indian groups have made millet a staple of their meals, with millet-based foods and recipes being passed down through the years. Dishes like ragi dosa (fermented pancakes) and ragi mudde (finger millet balls) are not only staple foods but also significant cultural icons in areas like Tamil Nadu and Karnataka.

Foods made from millet have a long history in the region's culinary customs and are frequently served at religious ceremonies and festivals. Local culinary traditions are supported and cultural heritage is preserved when certain culinary practices are preserved. For instance, millet-based snacks and sweets are frequently made for celebrations like Diwali, which reflects their cultural significance.

Livelihood Generation

The production of livelihoods is greatly aided by millet cultivation, especially for small-scale farmers and rural populations.

The processing, marketing, and distribution phases of the millet value chain, in addition to millet farming itself, create jobs and support rural development.

According to a National Bank for Agriculture and Rural Development (NABARD) research, millet growing provides over 10 million Indian farmers with necessary income and jobs. In rural regions, millet-based products like flour, flakes, and ready-to-eat snacks generate more jobs through processing and marketing.

Market Opportunities

The demand for millet-based products has increased both domestically and internationally as a result of greater awareness of the nutritional advantages and climate resistance of millets. With yearly growth rates of roughly 10-12%, the millet market in India has grown dramatically (Mother of Grains: What Millet Teaches Us About Biodiversity, n.d.). According to Ceasar and Maharajan (2022) the domestic millet market is expected to grow from its estimated USD 1.2 billion in 2023 to USD 2.5 billion by 2028.

For farmers and business owners engaged in the production and processing of millets, this growing demand opens up new markets. Economic growth is produced by value addition in the form of millet-based products such convenience foods, gluten-free goods, and health foods. Businesses and entrepreneurs in India are investing more money in inventions based on millet, producing goods like beverages, snacks, and breakfast cereals made from millet.

Cost-Effective Farming

Compared to other cereal crops, millet requires less inputs, making it a more economical crop to grow. Millets may be cultivated in marginal soils with little chemical fertiliser and pesticide use, and they require less water and pest and disease control treatments. Examples of millet species that do well on nutrient-poor soils and lessen the requirement for expensive inputs are barnyard millet and kodo millet.

With their limited financial means, small-scale farmers greatly benefit from this cost-effectiveness.

Because millet farming requires less inputs, it is a more cost-effective production method for farmers looking to maximise their profits. When compared to the production of wheat and rice, millet farming can lower input costs by as much as 40%, according to a comparative analysis conducted by the Indian Agricultural Research Institute (IARI) in 2022.

5. NUTRITIONAL PROFILE OF MILLETS

As an asset to a balanced diet, millets are highly nutritious grains that provide important components such dietary fibre, proteins, vitamins, minerals, and antioxidants. They offer a substantial amount of dietary fibre, which is essential for maintaining good digestive health, controlling cholesterol, and controlling blood sugar (Chandrakar & Shahi, 2023). For instance, finger millet has around three times the amount of fibre per 100 grammes (11–13 grammes) as white rice (Gahalawat et al., 2024). Millets are an essential source of protein, particularly for vegetarians and vegans, as they have a high protein content of 8 to 12 grammes per 100 grammes. Protein content of 11 grammes for pearl millet and 12 grammes for proso millet per 100 grammes includes lysine, an amino acid that is frequently deficient in cereals (Gahalawat et al.,2024). Compared to other grains, finger millet has a greater iron content of up to 3.9 mg per 100 grammes, whereas foxtail millet provides roughly 114 mg of magnesium and 285 mg of phosphorus per 100 grammes (Chandrakar & Shahi, 2023). They also include antioxidants like flavonoids and phenolic compounds, which lower the risk of chronic illnesses including diabetes and heart disease as well as oxidative stress. Millets are linked to better metabolic health and a decreased risk of developing chronic illnesses when consumed on a regular basis (Saleem et al., 2023).

6. CHALLENGES IN MILLET CULTIVATION IN INDIA

India's millet crop has enormous potential for rural development and sustainable agriculture. However, a number of issues prevent it from being widely used and from being as productive as it may be. These difficulties include the effects of climate change, insufficient research and development, low market demand, poor infrastructure, and problems with managing diseases and pests.

Low Market Demand and Infrastructure

The limited market demand for millets, which is a result of dietary preferences shifting towards more common grains like rice and wheat, is one of the key obstacles to millet farming. Because of this shift in preferences, there is a smaller market for millets, which drives down prices and deters farmers from growing them. Just 6% of India's total cereal consumption in 2023 came from millets, compared to 48% from rice and 38% from wheat (Yadav et al., 2023).

This problem is made worse by insufficient market infrastructure. Millets are poorly suited for market integration, processing, and storage, which makes it challenging for farmers to get reasonable pricing for their produce. Just 20% of millet farmers have access to suitable storage facilities, and even fewer have access to contemporary processing machines, according to a 2018 National Institute of Agricultural Marketing (NIAM) report. Farmers are discouraged from extending their millet farming due to post-harvest losses and limited marketability caused by this lack of infrastructure. More comprehensive strategies are required to ensure that farmers can profitably market and sell their millet crops, even with the help of government programs like the "Millet Mission" (Yadav et al., 2023) to close these gaps.

Limited Research and Development

Research and development spending on millets has been comparatively lower than that on main cereal crops like wheat and rice. The availability of enhanced millet varieties, agronomic techniques, and value-added products is restricted as a result of this neglect. Historically, research endeavours have been directed towards crops with high yields and great demand, neglecting millets in the pursuit of genetic enhancement and technical progress.

According to a survey conducted by the Indian Council of Agricultural Research (ICAR), millets received fewer than 5% of all agricultural research funds over the previous ten years. Millet producers currently face a shortage of high-quality seeds, inadequate technical expertise, and antiquated agronomic methods as a result of this underinvestment. Increasing productivity and profitability requires the creation of new millet varieties with larger yields, superior nutritional profiles, and improved resistance to pests.

Pest and Disease Management

According to other cereal crops, millets are generally more resistant to pests and diseases, but they are not completely impervious. Farmers may still face difficulties as a result of some illnesses and pests that might reduce millet harvests.

This problem is exacerbated by a lack of awareness and access to efficient pest and disease management techniques. Many millet farmers use antiquated techniques to manage pests, which might not be enough to handle contemporary farming issues. According to a National Agricultural Research System (NARS) survey, just thirty percent of millet farmers had access to contemporary methods of controlling pests (Balaguru, n.d.).

Creating and distributing integrated pest management (IPM) solutions, making bio-pesticides accessible, and educating farmers on optimal practices are all necessary to improve millets' resistance to pests and diseases. Agricultural NGOs and government extension agencies may be extremely helpful in teaching farmers and giving them the tools they need to properly manage diseases and pests.

Climate Change and Water Availability

India's millet crop faces serious challenges due to climate change. Even though millets are naturally suited to dry, arid environments, their development and productivity can still be impacted by extreme weather, erratic rainfall patterns, and water constraint. Even though pearl millet is drought-tolerant, extended dry spells or excessive rains may result in lower yields.

India has witnessed more frequent and severe weather events in the past several years, such as heatwaves and erratic monsoon rains, which have had an effect on agricultural output. According to data from the Indian Meteorological Department (IMD), throughout the previous 20 years, average annual rainfall in important millet-growing regions has dropped by roughly 5–10%. Because of this unpredictability, millets are less productive and dependable as a staple crop in terms of planting and harvesting schedules (Yadav et al., 2024).

Socio-Economic Barriers

Apart from the agricultural obstacles, socio-economic constraints also impede the cultivation of millet. Many farmers may not have access to finance or the necessary funds to invest in millet production. In comparison to farmers cultivating more popular crops like rice and wheat, millet-growing regions are frequently marginalised, which implies that farmers in these areas do not receive enough support or subsidies.

The customs and knowledge related to millet farming have also been undermined by the societal movement towards more widely consumed grains. The benefits of millets are generally not well known, and younger generations in rural areas are less familiar with the methods of millet production. To rekindle interest in millet cultivation and inform farmers and customers about the nutritional and financial advantages of millets, educational programs and extension services are required.

7. OPPORTUNITIES OF MILLET CULTIVATION IN INDIA

India has a lot of potential to boost economic growth, support sustainable agriculture, and improve nutritional security through the growing of millets. Growing consumer awareness of millets' health advantages and environmental resilience highlights the possibility for growing millet production and incorporating these ancient grains into contemporary food systems.

Organic and Value-Added Products

Considering millets require little chemical input and are under pressure from pests and diseases, they are especially well-suited for organic farming methods. This compatibility gives farmers the chance to practise organic farming and access high-end markets for organic goods. Millet growers may look forward to prosperous market opportunities due to the growing demand for organic foods, which is fuelled by customer preferences for sustainability and health.

Value-added millet goods, like flour, flakes, snacks, and prepared meals, increase the crop's economic worth and give farmers more sources of revenue.

Millets, being naturally gluten-free, fit in ideally with the growing global demand for health-conscious and gluten-free meals (Patra et al., 2023). Millet-based products are being creatively innovated by Indian food corporations and entrepreneurs, resulting in high-value products such as millet pasta, cookies, and energy bars. These products increase millets' marketability by appealing to urban consumers looking for quick and wholesome dietary options.

Rural Employment and Livelihoods

Growing and processing millets has the potential to improve rural livelihoods and provide jobs in rural areas. Businesses based on millet, such as processing facilities, businesses that produce value-added products, and chains of restaurants based on millet, generate employment possibilities and support the growth of the rural economy. Value addition and millet processing can raise farmer incomes by 20–30%, according to a National Bank for Agricultural and Rural Development (NABARD) research.

Policy Support and Government Initiatives

The Indian government is aware of how millets may support sustainable agriculture and increase food security. The National Food Security Mission (NFSM) and the Millet Mission are two initiatives that seek to encourage millet planting by means of enhanced seed distribution, market development, and subsidies. Farmers are encouraged by these regulations to cultivate millets and include them into public distribution systems and government nutrition programs.

More farmers may choose to plant millets as a result of the inclusion of millets in programs like the Public Distribution System (PDS) and the Mid-Day Meal Scheme, which can increase demand and consumption (Millets in PDS a Game Changer for Combating Malnutrition, Climate Change, n.d.). The government can promote rural livelihoods, improve nutritional results, and increase agricultural sustainability by aligning policy frameworks with the promotion of millets.

CONCLUSION

In light of climate change, millets are crucial for both sustainable agriculture and food security. They are especially useful in areas with harsh environmental conditions because of their resistance to drought, extreme heat, and poor soils. Millets are high in dietary fibre, protein, vitamins, minerals, and antioxidants that contribute to improved dietary diversity and the fight against malnutrition. Those who manage diabetes and gluten intolerance benefit from their low glycaemic index and gluten-free composition.

India has a long history with millets, which are currently seeing a renaissance thanks to government programs, consumer awareness, and the UN's 2023 International Year of Millets. Millets are now a part of both traditional diets and contemporary food systems because to this revival.

Millets have a positive environmental impact by promoting biodiversity, healthy soil, water conservation, and carbon sequestration. By promoting agroecological methods and using less chemical inputs, they lessen the agricultural footprint. Through opportunities in organic farming, value-added products, and agro-ecotourism, they improve rural livelihoods economically. The potential of millet products is further enhanced by the growing market demand for them, which is encouraged by policies and initiatives.

A comprehensive solution to food security, environmental sustainability, and economic growth can be found in millets. Because of these advantages, they are essential for tackling malnutrition, fostering sustainable practices, and creating a resilient agricultural future. Adopting millets helps to protect traditional agricultural and cultural legacy, which opens the door to a more robust and nutrient-dense global food chain.

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CHAPTER 4
DROUGHT FORECASTING FOR WATER SUSTAINABILITY: AN AI APPROACH APPLIED TO THE MEDITERRANEAN CONTEXT

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INTRODUCTION

Climate change often manifests itself in the increasing frequency, severity and duration of drought episodes worldwide, characterized by a period of low humidity in the natural climatic cycle. It unfolds progressively and is characterized by a decrease in precipitation, leading to a deficit in water availability (Wilhite&Vanyarkho, 2000). Recent research indicates that in many parts of the world, the geographical extent, probability and duration of droughts are set to increase over the next few years (Dai, 2013; Touma, Ashfaq, Nayak, Kao, &Diffenbaugh, 2015).

According to different disciplinary perspectives, the definition of drought that can occur can be classified into four groups, each with its own specific characteristics. Firstly, we find meteorological drought, which is associated with a lack of precipitation, with a prolonged period of low precipitation per compared to normal. In the second group, we find hydrological drought, which translates into a lack of water resources in rivers, lakes and groundwater. It occurs when rainfall is insufficient for a long period. Thirdly, the severe lack of soil moisture can be referred to as agricultural drought, which impairs the growth of vegetation cover and crops (Wilhite et al, 1987). Finally, the effect of water scarcity on human activities and social and economic systems is referred to as social and economic drought, which has many negative socio-economic repercussions. Drought preparedness and mitigation depend primarily on real-time information on the onset, progression and extent of drought, which can be generated by drought monitoring. This monitoring is carried out at through different types of drought indices, providing decision-makers with information on drought severity, frequency and duration, which can be used to trigger a contingency plan in case of availability (Kumar Daksh et al., 2018).

In the study of drought, several indices are used to quantify and monitor drought conditions. Among the most commonly used indices are the Standardized Precipitation Index (SPI), the Plant Water Stress Index (PHDI) and the Potential Precipitation Evapotranspiration Index (PDSI). These indices characterize the intensity, duration and severity of drought in a given region.

In recent years, the use of AI artificial intelligence models has increased for the estimation of hydrological parameters, including river flows, groundwater levels, precipitation, drought monitoring.etc (Apaydin et al., 2021; Nourani et al., 2014) (Bachir.S et al.,2021) (Sakaa.B et al 2020) . This is due to the ability of these models to improve the accuracy of predictions and contribute to the understanding of complex hydrological processes. Among the characteristics of the drought phenomenon, we note that it is multivariate, non-linear and random. Consequently, several machine learning models have shown promise for accurately predicting drought conditions using various indices, such as the Standardized Precipitation Index (SPI), the Precipitation and Evapotranspiration Drought Index (SPEI), Standardized Streamflow Index (SSI), Palmer Modified Drought Index (PMDI) and Palmer Drought Severity Index (PDSI).

The current state of research into drought prediction models represents an in-depth study of the advances, methodologies and practical uses of these predictive models. Given the increasing impact of human activities and climate change, accurate drought forecasting has become indispensable for efficient water resource management, sustainable agricultural strategies and minimizing risks to affected populations.

In this chapter, we present and discuss the results of drought index forecasting for Three stations: Ain El hadjel station, Msaad station and Boussaada station, in the Hodna basin in Algeria, using three different types of efficient machine learning approaches evolving in artificial neural networks (ANN), Random Forest (RF) and Spport Vector Machine (SVM).

1. MATERIALS AND METHODS

In this study, SPI values were calculated from monthly rainfall data from meteorological stations in the Hodna basin in Algeria between 1981 and 2020. This basin has a distinct Mediterranean climate that tends to be arid in nature. The basin covers an area of 26,000 km² southeast of the capital Algiers, and lies between 36°11' and 34°29' north latitude and between 3°2' and 6°11' east longitude. Msaad station was choosed as an exemple in Hodna basin in this study.

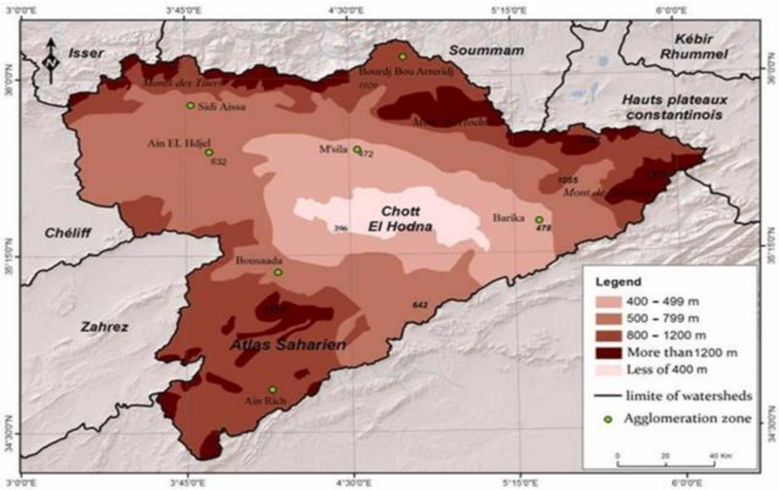

Figure 1. Hodna basin location map

2. METEOROLOGICAL DATA COLLECTION FOR DROUGHT FORECASTING

Meteorological data collection includes various parameters: precipitation, humidity (RH), temperature (RT), surface pressure (SP) and wind speed (WS) for the period between 1981 and 2020. Precipitation was used to calculate SPI6 and SPI12 for the Msaad station. (Table 1)

Table 1. Statistics of the gathered factors for Msaad station (1981-2020)

Msaad station	RH (%)	SP (Kpa)	WS (m/s)	RT (°C)
Minimum	17.000	92.660	2.510	16.500
Maximum	77.690	94.540	6.160	36.510
Mean	46.009	93.357	4.221	24.828
Median	45.285	93.320	4.210	24.540
Standard deviation	15.478	0.283	0.598	3.332
Kurtosis	-1.155	1.388	-0.090	0.030
Coefficient of variation	0.336	0.003	0.142	0.134

3. SPI CALCULATION

The concept of drought can be mathematically understood by means of indices that take into account the meteorological and socio-economic aspects of drought. In recent years, various drought indices have been developed. Generally speaking, a drought index is used to assess the impact of a drought and determine various aspects of drought conditions, such as intensity, duration, severity and geographical scope (Mishra et al., 2010).

The SPI was used to quantify the rainfall deficit in the Hodna basin. To calculate the SPI, long-term data over 40 years (1981-2020) were used. The standard procedure was first to fit the given rain gauge into a probability distribution function as described by McKee et al., (1993).

In this study, a data set covering three months was used. Subsequently, SPI values were calculated and used to assess and categorize droughts. The preference for the Gamma distribution function in this research was based on its effective integration with precipitation time series data (Bordi & Sutera, 2007). The Gamma distribution is expressed in terms of its probability density function as :

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} for x > 0 (1)$$

In this expression, αrepresents the shape parameter, βis the scale parameter, xrepresents the amount of rain in millimeters, Γ(α) is the resulting value of the gamma function, and -x corresponds to the average precipitation in millimeters.

The Γ(α) value is determined by a standard mathematical equation known as the Gamma function. This calculation is derived by employing an integral function according to the approach described by (Cacciamani et al., 2007) expressed as follows:

$$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y} dy (2)$$

In this context, y represents the result obtained from equation 1, indicating that y is equivalent to g (x). The Gamma function provided in equation 2 was evaluated by a numerical approach, using tabulated values depending on the shape parameter α.

Determining the optimal values for α and β involved applying a maximum likelihood approach, as described in equations 3 and 4 :

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right)(3)$$

$$\beta = \frac{\bar{x}}{\alpha}(4)$$

Where ;α, β and x retain the same meaning as defined in equation (1), and A represents a sample statistic. The calculation of the sample statistic is established through the relationship :

$$A = \ln(\bar{x}) = \frac{\ln(x)}{n}(5)$$

Where; n represents the number of observations. The probability density function g(x) in equation 1 is integrated with respect to x to obtain an expression for the cumulative probability g(x). This function is applicable when a particular amount of rainfall is received during a specific month and duration. Consequently, calculated cumulative probability values for non-zero rainfall are determined using equations 6 and 7, respectively.

$$g(x) = \int_0^x x^{\alpha-1} e^{\frac{-x}{\beta}} dx(6)$$

Where; $g(x)$ represents the cumulative probability of non-zero precipitation. Application of the gamma function is valid for precipitation values x > 0 in the considered time series of the basin. For non-zero values, the cumulative zero and non-zero probabilities are calculated. This probability is represented by the function H(x), defined as :

$$H(x) = q + (1 + q)F(x, \alpha, \beta)(7)$$

Where; H(x)represents the cumulative probability and q is the probability of zero precipitation. In this case, taking m as the number of zero occurrences in the time series of precipitation data, the nm ratio was used to estimate the probability q.

Next, the cumulative probability was converted to a standard normal distribution, such that the mean and variance of the SPI values are zero and one respectively. To achieve this transformation, an approximation based on the method of Mishra and Desai was adopted using the following equations :

$$SPI = -\left(K - \frac{C_0 + C_1 k + C_2 k^2}{1 + d_1 k + d_2 k^2 + d_3 k^3}\right) for\ 0 < H(x) \leq 0.5 (8)$$

$$SPI = +\left(K - \frac{C_0 + C_1 k + C_2 k^2}{1 + d_1 k + d_2 k^2 + d_3 k^3}\right) for\ 0.5 < H(x) \leq 1 (9)$$

The value of k was determined using equations 10 and 11 formulated as follows:

$$k = \sqrt{ln\left(\frac{1}{H(x)^2}\right)} for\ 0 < H(x) \leq 0.5 (10)$$

$$k = \sqrt{ln\left(\frac{1}{1 - H(x)^2}\right)} for\ 0.5 < H(x) < 1 (11)$$

In this study, SPI values were evaluated using a monthly time step and the threshold criterion presented in Table 3 was used to define drought conditions (Mckee et al., 1993).

To demonstrate the temporal variation of drought at different time scales (6 and 12 months) in the Hodna basin, SPIs for the Msaad station were generated and presented in Figure 2.

SPI values indicate wet and dry periods, with positive values indicating precipitation above the median and negative values indicating precipitation below the median. Severity classes for SPI values are categorized according to standard deviation from medians. This information is crucial for assessing and monitoring water conditions on different time scales. These classifications help identify the onset, duration, and intensity of drought or wetness events. Consequently, SPI serves as a valuable tool for supporting water resource management and informing climate-related decision-making.

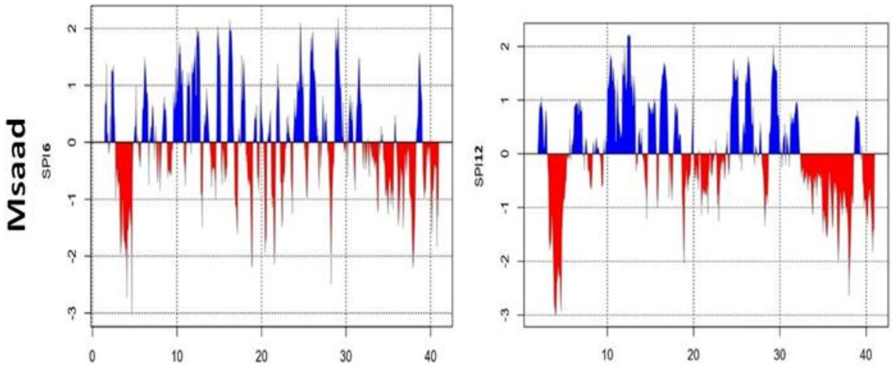

Figure 2. SPI time series at 6 and 12 months

4. FEATURE SELECTION

Feature selection is a key stage in the construction of machine learning models. It consists in choosing the most relevant variables (or "features") from all those available, in order to improve the model's performance.

After the calculation of SPI 6 and 12 the approache of feature selection was applied to choose the best combinaison of inputs the results shown in the table improved that the best combinaison is by taking 6 aniticipating of lead times (Table 2)

Table 2. Feature selection approache for Msaad station

Model	Predictors	R^2	AIC
1	$SPI12_{t-1}$	0,85	424,42
2	H, $SPI12_{t-1}$	0,85	414,06
3	SP, RH, $SPI12_{t-1}$	0,86	388,60
4	SP, RH, RT ,$SPI12_{t-1}$ $SPI12_{t-4}$	0,87	383,57
5	SP, RH, RT, $SPI12_{t-1}$ $SPI12_{t-3}$ $SPI12_{t-4}$ $SPI12_{t-5}$	0,87	380,25
6	SP, RH, RT, WS $SPI12_{t-1}$ $SPI12_{t-3}$ $SPI12_{t-4}$ $SPI12_{t-5}$ $SPI12_{t-6}$	0,88	370,04

5. MACHINE LEARNING MODELS

In recent years, the increasing use of artificial intelligence models for estimating hydrological parameters, such as river flows, groundwater levels and precipitation, has attracted attention (Apaydin et al., 2021).

This trend is explained by the ability of these models to improve forecasting accuracy and offer new insights into complex hydrological processes. Drought, in particular, is characterized by its multivariate, non-linear and unpredictable nature. As a result, numerous machine learning models have demonstrated their potential for effectively predicting drought conditions based on a variety of indices. These models include neural networks (ANN) (Hosseini-Moghari and Araghinejad, 2015; Mishra and Desai, 2006), support vector machine (SVM), adaptive neural fuzzy inference system (ANFIS) (Ali et al., 2018), random forest (RF) (Rhee and Im, 2017), Extrem machine learning (ELM) (Ladouali.S et al., 2024), decision trees (DT) (Gyaneshwar et al., 2023) and support vector regression (SVR) (Xu et al., 2018), many of these models have been applied and compared in numerous drought studies.

Three artificial intelligence models ANN (Artificial Neural Network), SVM (Support Vector Machine) and RF (Random Forest) were used to assess their ability to forecast drought indices SPI6 and SPI12 at the M'saad station, located in the Hodna basin. To calibrate the models, the data were divided into two sets: 70% for training and 30% for testing, enabling the performance of each model to be analyzed in the learning and validation phases.

Artificial Neural Network (ANN)

It's a model inspired by the human brain, composed of layers of interconnected neurons. It learns by adjusting the connections between neurons based on data (Dong, J., & Hu, S. 1997). it consists of neurons organized in layers (input, hidden, output) which receive data, weight them, apply an activation function and then transmit the result. In the supervised learning phase, the network adjusts its weights using backpropagation to minimize the error between predicted and actual values, enabling it to capture complex, non-linear relationships in forecasting, classification or regression problems. ANNs thus offer great flexibility and excellent performance for a variety of tasks, such as image recognition or drought index prediction. However, they remain poorly interpretable, greedy in data and computing power; if not properly tuned, they can also overlearn (overfitting) and lose generalizability.

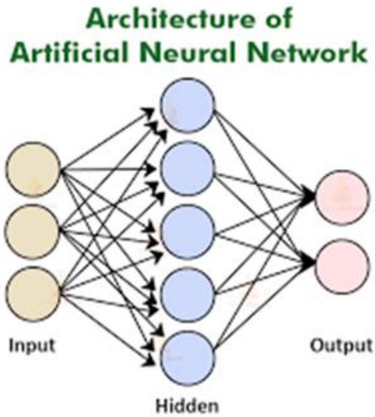

Figure 3. Architecture of Artificial Neural Network

Support Vector Machine (SVM)

An algorithm that seeks to find the optimal boundary between classes or to predict a value. Highly efficient for small data sets with good accuracy. Often gives very good results in regression and classification (Vapnik. 1995). Support vector regression (SVR) is an adaptation of the SVM model for regression problems. It is widely used in the literature to model continuous relationships between variables. The objective of SVR is to estimate a dependence function

$$F = \{f | f(x) = (w, x) + B \quad w \in R^n\} \qquad R^n \to R$$

Where w and B show a weight vector and a coefficient that have to be estimated from the data.Herein, the fundamental problem is to find a function f(x) that minimizes a risk function:

$$R[f(x)] = \int l(y - f(x), x) dP(x, y)$$

Where l is a loss function used to measure the deviation between the target, y, and estimate, f(x),values.

Random Forest (RF)

It's an ensemble model based on several decision trees, where each tree gives a prediction, and the model makes an average or a vote (Devroye et al. 1996) Robust, handles noisy data well and avoids overlearning.

This definition shows that the Random Forest (RF) model is based on a combination of several classifiers in the form of decision trees. In the approach proposed by Breiman, each tree is built from a subset of training samples, accompanied by a specific random variable, denoted Θk for the Ke tree. These random variables are independent and identically distributed (i.i.d). Each tree thus becomes a classifier denoted. the decision function is :

$$H(x) = \arg\max_{Y} \sum_{i=1}^{k} I(h_i(x) = Y)$$

Where H x( ) is combination of classification model, i h is a single decision tree model, Y is the output variable, I( )· is the indicator function. For a given input variable, each tree has right to vote to select the best classification result.

6. PERFORMANCE CRITERIA

RMSE measures the mean difference between observed values and values predicted by a model. It is an indicator of absolute error.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

yi = observed value

$\hat{y}_i$ = predicted value

n = number of points

The lower the RMSE, the better the model. It is expressed in the same unit as the data.

NSE - Nash-Sutcliffe Efficiency

The NSE is an indicator that evaluates the overall efficiency of a model in reproducing observations. It ranges from -∞ to 1.

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

7. RESULTS AND DISCUSSION

A comparative analysis of the performance of the machine learning models (SVM, RF and ANN) applied to the SPI6 index forecast at the M'saad station has enabled us to assess their effectiveness in the training and test phases. The results show that the SVM model was distinguished by its superior accuracy, both on training and validation data (Figure 04).

Indeed, the relationship between observed and predicted SPI6 values shows that the SVM model shows a stronger correlation (closer to 1), indicating a higher ability to capture the actual dynamics of the drought.

Thus, in the context of the M'saad station and for short-term drought forecasting (SPI6), the SVM model proves to be the best performer, offering more reliable and consistent estimates. This result underlines its strong potential as a predictive tool for early drought management, particularly in semi-arid regions.

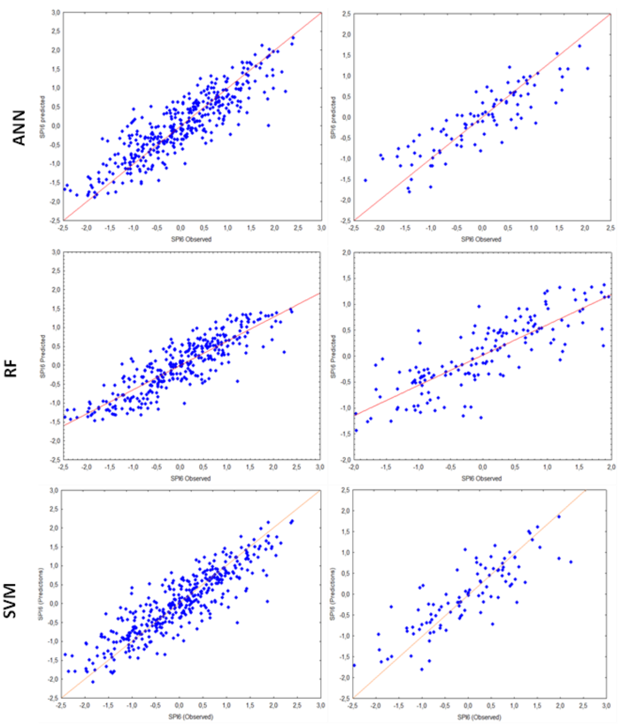

Figure 4. The relationship between observed and predicted SPI6 obtained from ANN, RF and SVM models in the training and testing stage at Msaad station

Evaluation of the performance of the SVM, RF and ANN models for forecasting SPI12 at the M'saad station shows that the SVM model also delivers the best results for this long-term index (Figure 05). Compared with the other approaches, SVM shows the highest correlation between observed and predicted values, as well as the lowest prediction errors, in both learning and test phases.

These results confirm the SVM model's ability to effectively model drought trends over long periods, making it particularly suitable for strategic management of water resources in sensitive climatic contexts.

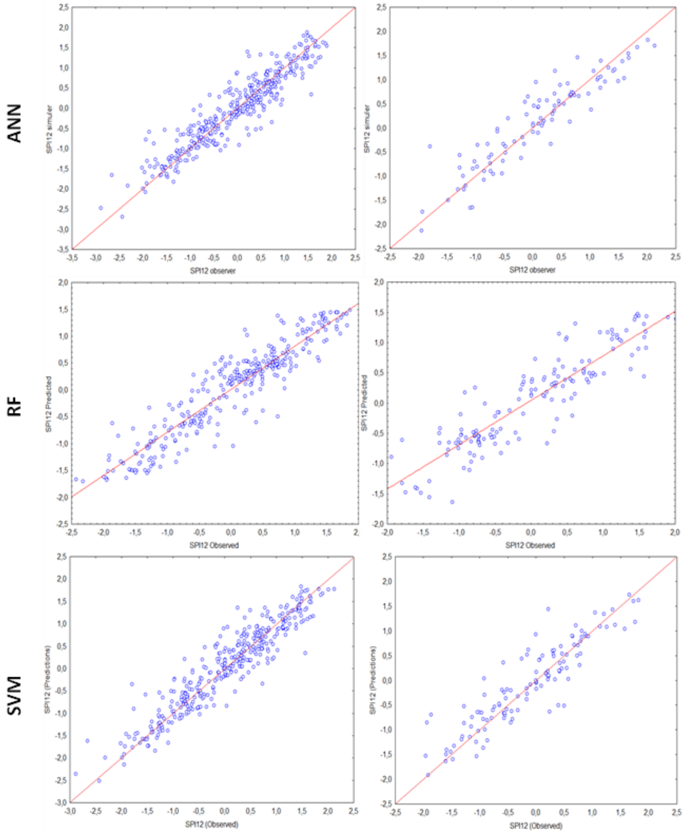

Figure 5. The relationship between observed and predicted SPI12 obtained from ANN, RF and SVM models in the training and testing stage at Msaad station

Prediction errors (RMSE, NSE) are lower for the SVM than for the RF and ANN models, reflecting better generalization. The SVM model is also more stable between the training and test phases, indicating good robustness and less overlearning.(Table 03 , Table 04)

Table 3. Performance criteria for modelling SPI6

Model	**Training**			**Testing**		
	R^2	**RMSE**	**NSE**	**R^2**	**RMSE**	**NSE**
ANN	0,76	0,48	0,76	0,75	0,47	0,75
RF	0,77	0,47	0,77	0,72	0,50	0,72
SVM	0,76	0,50	0,74	0,67	0,66	0,55

Table 4. Performance criteria for modelling SPI12

Model	**Training**			**Testing**		
	R^2	**RMSE**	**NSE**	**R^2**	**RMSE**	**NSE**
ANN	0,87	0,35	0,87	0,85	0,37	0,85
RF	0,88	0,34	0,88	0,81	0,36	0,81
SVM	0.87	0.36	0,86	0.82	0,42	0,81

CONCLUSION

Drought is a complex problem that affects not only ecosystems, but also economies and human societies. The consequences of drought, from loss of biodiversity to depletion of water sources, require a detailed understanding of the causes of these phenomena, based on both natural processes and human activity. Flexible, individualized interventions are needed to strengthen the ability of communities to withstand these extreme climatic events .

AI models, such as neural networks, fuzzy logic and support vector regression, are proving particularly effective in predicting complex drought events, capturing the non-stationary and non-linear aspects of the data.

The application of the ANN, SVM and RF artificial intelligence models for forecasting the SPI6 and SPI12 drought indices at the M'saad station enabled us to compare their effectiveness in a semi-arid context. The results showed that the SVM model stood out for its high accuracy, generalization capability and low prediction errors, both for the short term (SPI6) and the long term (SPI12).

The model is therefore proving to be a powerful and reliable tool for drought forecasting in the Hodna basin, and can contribute to better proactive management of water resources in the face of the challenges posed by climate change.

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