



Markov chain modelling of meteorological drought return periods: A case of Mberengwa district, Zimbabwe

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ABSTRACT

This study applies a first-order Markov chain modelling approach to Standardised Precipitation Index data derived from 2011 to 2021 annual rainfall data collected across the 37 wards in Mberengwa District, Zimbabwe, to assess its meteorological drought return period patterns. The study aims to estimate the meteorological drought return periods using the steady-state probabilities and calculate multiple-year drought probabilities and the expected duration of drought, providing a probabilistic understanding of drought dynamics to support effective drought risk management and climate adaptation planning in the district and other arid areas. The Standardised Precipitation Index values were classified into drought, normal and wet states based on their magnitudes. The transition probabilities were used to calculate the steady-state probabilities, which were used to estimate the return periods. The Markov Chain Property (Memoryless Property) and stationarity assumptions were validated using the autocorrelation graph and chi-square distribution, respectively. Each validation resulted positively supported the Markov chain assumptions, suggesting that the local authorities could rely on the model's predictions for planning and resource management. The findings indicated that drought conditions occur 23% of the time with a corresponding return period of approximately 4.35 years, normal conditions occur 59% of the time with a corresponding return period of approximately 1.69 years, and wet conditions occur 18% of the time with a corresponding return period of approximately 5.56 years. The probabilities of the multi-year droughts revealed a 24.7% chance of a drought lasting approximately 2 years, diminishing to 0.37% for five consecutive years. The expected length of drought was estimated to be 1.33 years, suggesting that while droughts are a concern, they often resolve relatively quickly. This study emphasises the need for local authorities to develop comprehensive emergency preparedness plans, invest in water conservation infrastructure and foster community engagement to enhance resilience against the impacts of climate variability.

Keywords: Climatic Variability, Drought Return Periods, Markov Chain Modelling, Standardised Precipitation Index, Steady-State Probabilities, Transition Probabilities

I. INTRODUCTION

Droughts are a recurrent challenge in Zimbabwe, particularly in semi-arid areas such as Mberengwa District and regions depend heavily on rain-fed agriculture, making them particularly vulnerable to meteorological droughts. (Moyo et al., 2021). The increased frequency and severity of droughts in recent years have necessitated a deeper understanding of drought return periods, which refer to the average time intervals between occurrences of droughts of similar intensity. Drought is one of the inseparable elements of climate fluctuation that causes a lot of damages every year. Drought is basically caused by the lack of precipitation events in a region over a period and can be regarded as an extreme climatic event. The early stages of accumulated precipitation deficiencies are referred to as meteorological drought being a region-specific natural event, since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region (Dalezios et al., 2017). Considering the effects of drought on different parts of the environment, agriculture, natural resources, wildlife, etc., drought forecast can be useful for managing the crisis and reducing its damages (Javadinejad et al., 2023).

Meteorological droughts are characterised by a significant lack of precipitation, have wide-reaching impacts, including crop failures, water shortages and social instability. In Mberengwa District, repeated drought episodes have led to crop failures, reduced water availability and heightened food insecurity, underscoring the need for effective drought monitoring and management tools. Despite the growing need for such analysis, few studies have applied Markov chain modelling to drought assessment in Zimbabwe, and even fewer have focused on the district level, where local adaptation strategies are most needed. Droughts are complex, multifaceted, slow-onset hazards that can last for several months or years, affecting wide geographic areas and a lot of people, with severe consequences for human lives, the environment, and the economy (Hagenlocher et al, 2019). Prediction of drought class transitions has been received

increasing interest in the field of water resource management and Markov chain models are effective prediction tools that are widely used to analyse drought class transitions by describing the temporal dependency of drought events (Yang et al., 2020).

Quantitative analysis provides an objective assessment of meteorological drought conditions and impacts, reducing personal biases and subjective interpretations (Wilhite & Glantz, 1985). It also enables comparisons across different time periods, locations and drought events, facilitating the identification of patterns and trends (Svoboda & Fuchs, 2016). This research aims to address this knowledge gap, by using a quantitative approach which is objective and scalable to understand the meteorological drought return periods and impacts in Mberengwa. While SPI provides a snapshot of drought intensity (Quiring, 2009), it does not directly capture the temporal dynamics or transitions between drought and non-drought states. To address this gap, Markov chain modelling offers a statistical approach to analyse (Paulo & Pereira, 2007) the dynamics of drought occurrence, persistence and return periods. By estimating the likelihood of moving from one climate state to another over time, Markov models provide deeper insights into drought risk patterns essential for early warning and adaptation planning. Over recent decades, Zimbabwe has faced increased climate variability and frequency of extreme weather events, including severe droughts. Studies have linked these changes partly to global climate change, which has altered rainfall distribution and intensified dry spells in many parts of southern Africa

1.1 Statement of the Problem

Meteorological droughts have become increasingly frequent and severe in Mberengwa District, Zimbabwe, disrupting agricultural productivity and threatening water security and rural livelihoods. The current methods for predicting drought and assessing their return periods may not fully capture the complex and stochastic nature of drought events in the region. This gap hampers effective drought risk management and adaptive planning. This study addresses these challenges by applying Markov chain modelling (Yang et al., 2020), Javadinejad et al., 2023) to model drought as a sequence of transitions between drought, normal and wet states, measurement of drought dynamics and provide actionable knowledge for building resilience in Mberengwa District, Zimbabwe

1.2 Research Objectives

- i. To calculate the steady-state probabilities derived from transition probability matrix for understanding the long-term behaviour of meteorological droughts return periods.
- ii. To calculate the return periods of meteorological drought events for evaluating their frequency and implications for resource management.
- iii. To investigate the probabilities associated with multi-year drought occurrences for drought risk assessment.
- iv. To calculate the expected duration of drought events based on transition matrix analysis to inform planning and preparedness efforts in affected areas.

II. LITERATURE REVIEW

2.1 Theoretical Review

Meteorological drought is defined by Wilhite and Glantz (1985) in terms of four basic approaches to measuring drought: *meteorological*, *hydrological*, *agricultural* and *socioeconomic*. The first three approaches focus on ways to measure drought as a physical phenomenon. The last deals with drought in terms of supply and demand, tracking the effects of water shortages in socioeconomic systems. Meteorological drought is usually defined depending on the degree of dryness (in comparison to some “normal” or average amount) and the duration of the dry period and must be considered as region-specific since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region (Wilhite & Glantz, 1985)

Socio-economic impacts of meteorological drought return periods are devastating. They severely affect agricultural productivity and revenue, leading to crop failures, reduced yields, livestock deaths, increased food prices and malnutrition among vulnerable populations such as children and the elderly (Food and Agricultural Organization [FAO], 2017; World Food Programme [WFP], 2020). Drought also causes migration and displacement of communities in search of water and livelihoods leading to increased poverty and mental health among the vulnerable populations and (WHO, 2018). Moreover, drought enhance the increase the risk of water-borne diseases, respiratory problems and other health issues related to poor air quality and dust..

Ayugi et al. (2022) examined the state of meteorological drought over Africa, focusing on historical trends, impacts, mitigation strategies and future prospects. The resultant impact was evidenced in the decline of agricultural activities and water resources and the environmental degradation across all subregions. They suggested efficient delivery service to drought-prone hotspots, strengthening drought monitoring, forecasting, early warning, and response systems and improved research on the combined effects of anthropogenic activities and changes in climate in Africa today and in the future.

Bekana (2025) examined the critical drought impacts and its risk management in Ethiopia, a country that faces recurrent droughts fanned by climate change, significantly impacting millions of people, particularly in rural areas. They recommended the integration of drought management strategies that combine government initiatives, community engagement and international support to enhance resilience among vulnerable populations.

2.2 Empirical Review

2.2.1 Drought Monitoring Tools

The Standardized Precipitation Index (SPI) has become a widely accepted tool for quantifying drought conditions by standardizing rainfall anomalies over various time scales. There are many drought indicators and indices being used around the world and noted that it is recommended by the World Meteorological Organization to be used in monitoring and assessment of meteorological droughts, although it may not be accepted as the only and absolute index (Dalezios et al., 2017).

Mahmoudi et al. (2021) compared the performance of the Standardized Precipitation Temperature Index (SPTI) with the commonly used drought indices, the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) for 17 meteorological stations of Khyber Pakhtunkhwa (KPK) province in Pakistan. They found that SPTI is strongly correlated with SPI and performed better than SPEI in low temperature regions for detecting and monitoring drought conditions over different time scales.

Kubicz (2018) assessed the occurrence and intensification of meteorological drought conditions in both surface and groundwater systems using the standardized SPI index. Kubicz (2018) discovered that applying SPI for hydrogeological drought monitoring required to assess the significance and level of the correlation between drought indices in the test area and then to calculate the probability of correct determination of drought in surface and groundwaters with the use of SPI.

Brunner et al. (2019) assessed the short-term and long-term drought severity in Saudi Arabia using the Standardized Precipitation Evapotranspiration Index (SPEI) at multiple time scales and applied advanced statistical methods, including Innovative Trend Analysis (ITA), Wavelet Transform, and Bivariate Copula Models, to analyse drought patterns, periodicity and return periods. They revealed that vegetation and water resources are vulnerable to prolonged dry conditions, underscoring the urgent need for adaptive water management strategies.

2.2.2 Markov Chain Models

The Markov Chain Models have been employed to predict drought probabilities. Azimi et al (2020) presented a steady-state Markov chain model to predict the long-term probability of drought conditions. They proposed a rigorous framework for statistical analysis of drought characteristics and its trends over time for a large area of aquifers and plains in Iran. They revealed a rising trend in drought conditions with steady-state drought probabilities increasing.

Yeh and Hsu (2019) used the Standardized Precipitation Index (SPI) and the Standardized Groundwater Level Index (SGI) and employed the first-order Markov chain model and Wavelet transform to determine the drought characteristics and propagation, including the steady-state probabilities of drought events and the mean duration for the stations in southern Taiwan basins.

Javadinejad et al. (2023) calculated monthly droughts based on the standard precipitation index (SPI) in several stations in the south of Iran during the years 1980–2020. They used the Markov chain to forecast the monthly drought for the years 2020 to 2040. Most of the stations had normal, moderate and severe drought conditions. The transition probability matrix showed the probability of passing from wet to dry state was high while the probability of transition from dry to wet was low in all stations

2.2.3 Drought Return Periods and Severity

Zhou et al. (2022) used, the Palmer drought severity index (PDSI) method, in which the meteorological factors less influenced by human activities were taken as the input to determine the dry/wet states and the PDSI value at each period firstly in Huaipei Plain, China. They considered the drought severity and peak intensity as drought characteristics and the joint return periods of the characteristics were estimated based on the Gumbel-Hougaard copula function. Their results showed that the most severe droughts identified by PDSI had a good consistency with the actual drought situations, drought severity and peak intensity were applicable to reflect the drought impacts.

Brunner et al. (2019) analysed the 2018 drought in Switzerland across meteorological, hydrological, agricultural and groundwater types, focusing on discharge and soil moisture deficit and deficit duration through univariate and bivariate frequency analyses. Their results showed that the 2018 drought event was especially severe in north-eastern Switzerland in terms of soil moisture, with return periods locally exceeding 100 years. They concluded that the return period estimates depended on the region, variable, and return period considered.

Montaseri et al. (2018) evaluated systematically two Unconnected Drought Runs (UDR) and Connected Drought Runs (CDR) procedures in modelling the joint probability of drought duration and severity investigations using 24 rain gauges in Lake Urmia basin, Iran. Their results demonstrated a significant comparative advantage of the new

approach compared to the traditional approach. They concluded that the new method could enable them to estimate the joint/conditional probabilities of drought duration and severity and significant reduction in uncertainty for modelling more accurately.

2.2.4 Climate Change and Drought in Zimbabwe

Manyakaidze et al. (2025) determined the climate change impacts on farmer-managed wetland agroecosystems and evaluated the resilience-building strategies in semi-arid rainfall marginal areas, focusing on Nyororo wetland in Mberengwa district, Zimbabwe. Resilience-building strategies, including adopting seasonal livelihood programmes, ecosystems-based adaptation (EbA) strategies such as wetland farming, protection of wetland water sources, harvesting wetland goods for selling and anticipatory action planning (AAP), including planting drought-tolerant, short-seasoned food crops, proved effective in the sustainable management of wetlands agroecosystems. Hence, they recommended the tailoring of financial mechanisms to suit the needs of local communities' conservation and resilient livelihoods and that stakeholders should implement the promising wetland agroecosystem resilience-building strategies that bring positive outcomes for people, nature and climate.

Mupepi and Matsa (2022) assessed the seasonal spatio-temporal dynamics of agro-meteorological drought between 2017 and 2020 in Mberengwa and Zvishavane districts, Zimbabwe. Their results showed that both Mberengwa and Zvishavane districts experienced an increasing trend in spatial coverage of drought from 2017 to 2019 before a slight decline in 2020. From 2017, drought severity increased in terms of spatial coverage in both Mberengwa and Zvishavane districts between 2018 and 2020. Therefore, they concluded that drought is worsening in both Mberengwa and Zvishavane districts, hence, long-term drought resilience interventions are required to improve drought resilience of communities in these areas.

Kwami et al. (2018) assessed the impact of climate change on agriculture and the adaptation strategies by the farmers in a selected area in Mberengwa District, Zimbabwe. They identified increased incidences of livestock and crop pests and diseases, shorter rainy seasons and insufficient seasonal rains characterised by mid-season dry spells and more frequent severe floods which often destroyed crop fields. They suggested increasing the number of agricultural extensions, facilitation of the access to low-interest loans by eligible farmers to boost capital and small-scale irrigation schemes through the construction of small dams or the drilling of boreholes to improve water management in the area.

Muzerengi et al. (2023) explored the impacts of climate change on household food security among the vulnerable populations of Matande communal lands, Mwenezi district in Zimbabwe guided by the Sustainable Livelihoods Framework (SLF). The results demonstrated that climate change propelled increases of pests and diseases for both livestock and crops, reduction of meals uptake per day, biodiversity loss and dwindled crop production. They suggested adaptive measures for sustainable management.

III. METHODOLOGY

3.1 Research Design and Approach

This study employed a quantitative approach, using historical annual rainfall data and Markov Chain Modelling to analyse meteorological drought return periods in Mberengwa District, Zimbabwe. The data analysis was conducted using JASP (version 0.19.3.0) and Microsoft Excel.

3.1.1 Study Area

Mberengwa district is one of the eight districts in Midlands Province. It is in the southern part of the province. The district has a total area of 494,340 hectares and comprises 37 administrative wards as shown in Figure 1 below. Mberengwa District is a semi-arid region with low seasonal rainfall below 650mm. Precipitation falls from November to March, with the greatest amounts falling between December and February. The district is prone to drought and prolonged mid-season dry spells. Temperatures are generally high, usually reaching a maximum of above 38⁰C. Most of the households in Mberengwa rely on subsistence farming and livestock rearing for their livelihoods. Crop production is low due to moisture stress. ([Mberengwa-District-Profile.pdf,2023](#)).

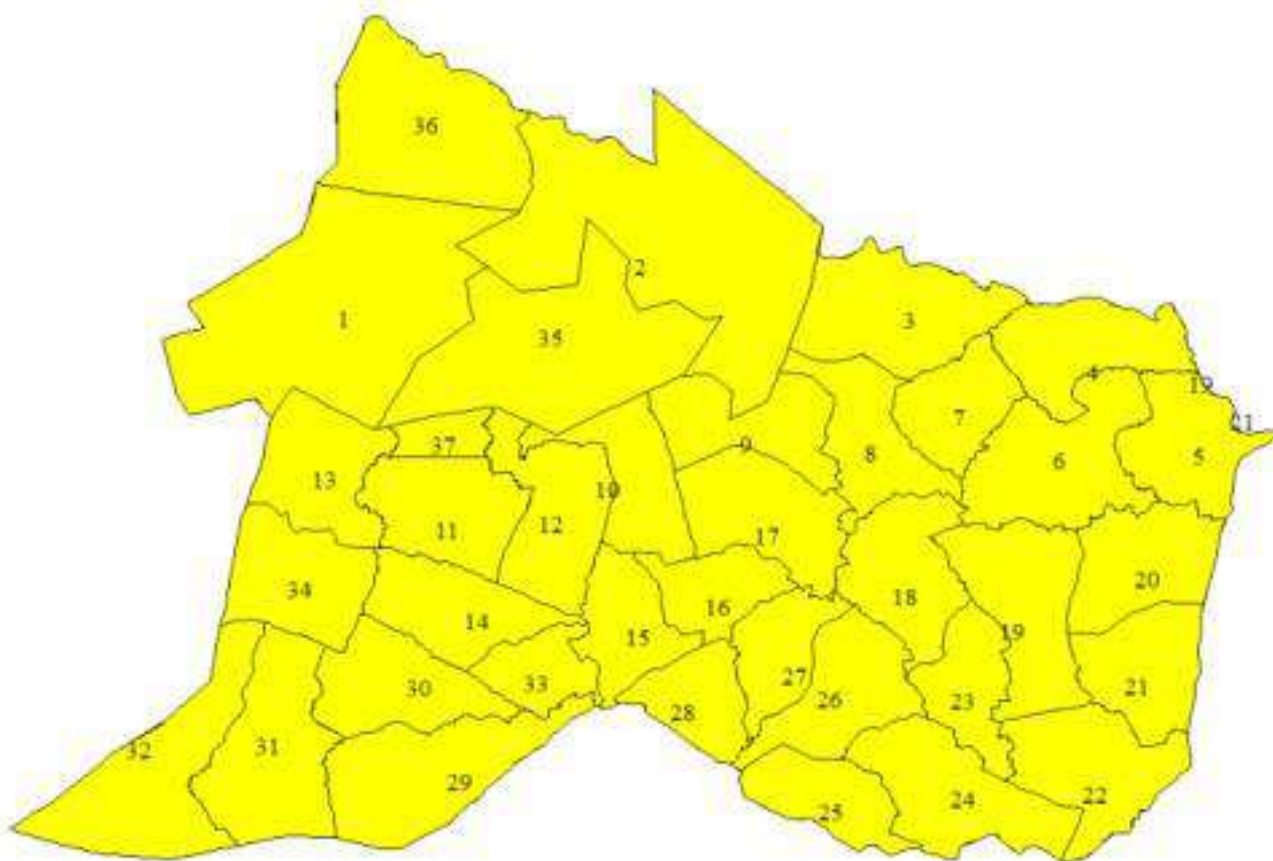


Figure 1
Mberengwa Administrative District Map
 Source: Mberengwa Rural District Council (n.d.)
<https://mrdc.org.zw/index.html>

3.2 Sampling Strategy

The study considered the 37 administrative wards in Mberengwa district, Zimbabwe. The annual rainfall data were sourced from the Meteorological Services Department of Zimbabwe, covering the years 2011 to 2021. The data collected from all wards provided a comprehensive view of rainfall patterns across the district.

3.3 Data collection

The annual rainfall data were obtained from the Meteorological Services Department of Zimbabwe and local climate databases in Mberengwa District, Zimbabwe. The data covered an 11-year period from 2011 to 2021. The annual Standardised Precipitation Index (SPI) was calculated from the Weibull-fitted rainfall data to analyse meteorological drought return periods. Markov Chain modelling was then applied to estimate drought transition probabilities; drought return periods and the expected length of drought for the district.

3.4 Data Analysis

3.4.1 Fitting the annual Rainfall Data to the Weibull Distribution

The annual rainfall data was first fitted to a Weibull distribution, which is suitable for modelling skewed hydrological variables like rainfall. The Weibull distribution was chosen because the Mberengwa rainfall data has frequent dry periods (zero rainfall) and moderate extremes, aligning with Weibull flexibility. Its shape parameter (k) allows it to model diverse rainfall events like zero rainfall and heavy precipitation events.

3.4.1.1 Parameter Estimation

The shape (k) and the scale (λ) parameters of the Weibull distribution were estimated using the Maximum Likelihood Estimation (MLE) in JASP (version 0.19.3.0) software.

3.4.1.2 Calculation of the Weibull Cumulative Distribution Function

The Weibull Cumulative Distribution Function was calculated using the formula:

$$F(x) = 1 - e^{-\left(\frac{x}{\lambda}\right)^k}$$



Where:

- $F(x)$ = cumulative probability of rainfall amount $\leq X$
- λ = scale parameter
- k = shape parameter
- x = observed fitted rainfall amount.

3.4.1.2 Converting Cumulative Distribution Function to Standard Normal Distribution

The cumulative probabilities were converted to a standard normal distribution using the inverse normal distribution. The resulting z-values represented the Standardised Precipitation Indexes, (SPIs), which indicates the number of standard deviations from the mean precipitation calculated from the annual rainfall data.

$$\text{Standardised Precipitation Indexes (SPI)} = \Phi^{-1}(F(x))$$

Where:

- Φ^{-1} is the inverse normal distribution function.
- $F(x)$ is the cumulative probability

3.4.2 Developing the Markov Chain Model

A Markov Chain model is a mathematical framework used to model stochastic (random) systems that transition between discrete states over time, where the probability of moving to a future state depends only on the current state, memoryless (Markov) property.

The SPI values were classified into three states based on their magnitudes: Drought (D): $\text{SPI} \leq -1$, Normal (N): $-1 < \text{SPI} < 1.0$ and Wet (W): $\text{SPI} \geq 1.0$. The Drought (D), Normal (N) and Wet (W) states smoothen the short-term SPI fluctuations, capturing persistent drought signals. These states align with operational drought management: Drought triggers water restrictions, Normal represent the baseline conditions and Wet represent flood risk or reservoir replenishment. The SPI values near ± 1 mark statistically significant deviations from the mean and ensure a balanced class size. The three states were chosen in line with the standardized drought classification. Fewer states reduce Markov Chain complexity. These states simplify to a 3×3 transition matrix which is easier to interpret and validate than larger matrices and avoids sparse transition probabilities with limited data.

3.4.2.1 Constructing the Transition Probability Matrix (TPM), (P)

The historical SPI time series data were used to calculate the probabilities of transitioning between drought, normal and wet, to form the Transition Probability Matrix (TPM), (P). The following steps were taken:

Recording count transitions

The possible nine count transitions between states were recorded:

$$D \rightarrow D, D \rightarrow N, D \rightarrow W$$

$$N \rightarrow D, N \rightarrow N, N \rightarrow W$$

$$W \rightarrow D, W \rightarrow N, W \rightarrow W \text{ where D is Drought, N is Normal, and W is Wet.}$$

The number of transitions between each pair of states was counted from one state to another in consecutive years.

Calculating Transition probabilities

The first-order Markov transition probabilities were calculated using:

$$P_{ij} = \frac{\text{Number of transitions from state } i \text{ to state } j}{\text{Total number of transitions from state } i}$$

The Transition Probability Matrix, a square matrix of order 3, from the three states, where rows sum to 1 was constructed. Transition probabilities p_{ij} representing the likelihood of moving from one state i at time t to state j at time $t+1$ were estimated:

$$P = \begin{bmatrix} P_{Drought,Drought} & P_{Drought,Normal} & P_{Drought,Wet} \\ P_{Normal,Drought} & P_{Normal,Normal} & P_{Normal,Wet} \\ P_{Wet,Drought} & P_{Wet,Normal} & P_{Wet,Wet} \end{bmatrix}$$

On the Transition Probability Matrix, rows represent the current state (drought, normal, wet) and columns represent the next -year state (drought, normal, wet)

3.4.2.2 Assumptions of the Markov Chain Model

Markov property (Memoryless): It assumes that future drought depends only on the current state not earlier states. *Stationarity Assumption* The model assumes that transition probabilities between the states (drought, normal, wet) remain constant over time. *Spatial homogeneity assumption:* It assumes that a single transition matrix is applied uniformly across the regions.



3.4.2.3 Validation of the Assumptions of the Markov Chain Model

The ACF (Autocorrelation Function) graph was used to test the Markov chain property in JASP (version 0.19.3.0) software, in which the Drought, Normal and Wet states were used as dependent values against Time (2011 to 2021) for Mberengwa district. The data exhibited the Markov property, which implies that future states depend only on the current state, not on the sequence of events that preceded it. The stationarity assumption was also validated using the chi-square distribution goodness-of-fit test, in which the observed transitions data were compared with the expected data using Microsoft Excel.

3.4.2.4 Drought return periods analysis

Calculating the Steady-State Probabilities, π

The steady-state probabilities represent the long-term proportion of time the system spends in drought, normal or wet states. They are calculated using the Transition Count Matrix data in Table 1. The steady-state probabilities are denoted by the vector:

$$\pi = [\pi_1, \pi_2, \pi_3, \pi_4 \dots, \pi_n]$$

The long-term probabilities were $\pi_{Drought}$, π_{Normal} and π_{Wet} where:

$\pi_{Drought}$ represents the proportion of time the district is expected to be in the drought state in the long run.

π_{Normal} represents the proportion of time the district is expected to be in the normal state in the long run.

π_{Wet} represents the proportion of time the district is expected to be in the wet state in the long run.

To find the long-term probabilities, $\pi_{Drought}$, π_{Normal} and π_{Wet} we solved:

$$\pi = \pi P \text{ where } P \text{ is the Transition Probability Matrix.}$$

This results in the system of equations:

$$\pi_1 P_{11} + \pi_2 P_{21} + \pi_3 P_{31} = \pi_1$$

$$\pi_1 P_{12} + \pi_2 P_{22} + \pi_3 P_{32} = \pi_2$$

$$\pi_1 P_{13} + \pi_2 P_{23} + \pi_3 P_{33} = \pi_3$$

$$\pi_1 + \pi_2 + \pi_3 = 1.$$

The linear equations were solved to find:

$$\pi_1 \text{ for the drought state, } \pi_2 \text{ for the normal state and } \pi_3 \text{ for the wet state.}$$

It was solved using numerical solvers in Microsoft Excel. Once calculated, the steady-state probabilities remained constant over time under the assumptions of the Markov process.

Computing the Drought Return Periods

The drought return period, also known as the recurrence interval, is the average time between occurrences of drought conditions that meet a specific severity threshold. It can be calculated using steady-state probability. The reciprocal of the steady-state probability gives the drought return period, T_i :

$$T_i = \frac{1}{\pi_i}, \text{ so } T_{Drought} = \frac{1}{\pi_{Drought}}$$

$$T_{Normal} = \frac{1}{\pi_{Normal}}$$

$$T_{Wet} = \frac{1}{\pi_{Wet}}$$

It indicates the frequency of drought, normal or wet occurrence respectively.

3.4.2.5 Drought Persistence Forecasting

Drought Persistence Forecasting involves predicting the likelihood that a drought state will persist over subsequent time periods based on transition probabilities in drought state.

The probability distribution of states after n steps, $\pi^{(n)}$ is used to predict the drought behaviour over n years. It is given by:

$$\pi^{(n)} = \pi^{(0)} \times P^n$$

$$\pi^{(n)} = \text{predicted state distribution after } n \text{ years}$$

$$\pi^{(0)} = \text{the initial state distribution}$$

$$P^n = \text{the transition matrix raised to the } n^{th} \text{ power.}$$

The one-step prediction, two-year step prediction and multi-step forecasting were estimated.

One-Year Persistence

It is the probability that drought will continue next year.

$$P(Drought) = P(Drought \text{ at } t + 1 | Drought \text{ at } t)$$

Two-year persistence

It is the probability that drought will continue for 2 more years.

$$P((Drought)^2) = P(Drought \text{ at } t + 1 \text{ and } t + 2 | Drought \text{ at } t)$$

Multi-year drought probability



A multi-year drought occurs when the drought state persists for 2 or more consecutive years.

K-year drought probability

Probability of a drought persisting k years (from time t to t+k-1):

$$P((Drought)^{k-1}) = P(Drought \text{ for } k \text{ years} | \text{start in Drought})$$

Probability of multi-year drought ending

It is the probability that a drought ends in the k^{th} year:

$$P((Drought)^{k-2}) \times (1 - P(Drought)) = P(Drought \text{ for } k - 1 \text{ years, exists})$$

3.4.2.6 Expected Length of a Drought (E(L))

The Expected length of a drought (E(L)) is the expected drought duration. It is calculated as the sum of probabilities of remaining in drought over successive years. The expected drought duration is calculated using the formula:

$$E(L) = 1 + P(Drought) + P((Drought)^2) + P((Drought)^3) + P((Drought)^4) + P((Drought)^5)$$

The formula indicates that the expected duration is a cumulative measure of the length of the persistence of the drought conditions.

3.5 Ethical Considerations

In conducting this study, ethical considerations were observed to ensure responsible research practices. All information obtained from the local climate databases and the Meteorological Services Department were used strictly for academic purposes without any manipulation or misrepresentation. Since the research involves no direct interaction with human participants, issues of privacy and consent were minimal. However, community -level information was anonymised to prevent stigmatisation of the wards which were perceived as highly drought-prone. The integrity of the data was also a focal point, adhering to ethical standards to accurately represent and cite all data sources while acknowledging potential biases in the analysis. The research aims to contribute positively to understanding drought patterns in Mberengwa District, Zimbabwe, by generating knowledge that informs adaptation strategies and enhances resilience to climate variability for better agricultural practices and policy decisions to benefit the local community.

IV. FINDINGS & DISCUSSION

4.1 Pre-processing of Data

It involved transforming, cleaning and formatting data to prepare it for analysis or modelling. The data was organised in chronological order in a spreadsheet in Microsoft Excel, with each row containing the year and its corresponding SPI value. The missing SPI entries were identified and imputed appropriately. No outliers were identified. It emphasises the importance of data integrity in drought analysis as mentioned by Mahmoudi et al. (2021) in their research.

4.2 Transition Count Matrix

Table 1

Transition Count Matrix

From/To	Drought	Normal	Wet	Total
Drought	24	53	20	97
Normal	58	149	34	241
Wet	15	39	15	69

Table 1 above shows the observed number of transitions between states (Drought, Normal, Wet). The Transition Count Matrix provided the insights into how the states transitioned from one to another over 11 years (2011 to 2021). It shows that Drought → Drought transitions occurred 24 times, Drought → Normal transitions occurred 53 times, which is more than that remaining in Drought (24), indicating that it is feasible to recover from drought, but it is not guaranteed, aligning with Ayugi et al.(2022), who noted the dynamic nature of drought conditions in Africa. Drought → Wet transitions occurred 20 times, suggesting that such extreme recovery is less frequent. Normal → Drought transitions occurred 58 times, which shows a large risk of returning to Drought from Normal. It has relevance for policy planning and water resource management as suggested by Bekana (2025). Normal → Normal transitions occurred 149 times, Normal → Wet transitions occurred 34 times, Wet → Drought transitions occurred 15 times, Wet → Normal transitions occurred 39 times, Wet → Wet transitions occurred 15 times. The Normal state exhibits a larger number of transitions (241) with a strong inclination to remain in Normal (149). This implies that the average climatic conditions are the most stable state. The matrix represents a dynamical system in which the climate alternates between states emphasizing the importance of monitoring climatic changes and preparing for potential drought risks.



4.2 Transition Probability Matrix (P)

Table 2

Transition Probability Matrix (P)

From/To	Drought	Normal	Wet	Total
Drought	0.247	0.547	0.206	1
Normal	0.241	0.618	0.141	1
Wet	0.217	0.566	0.217	1

Table 2 shows a transition probability matrix, with probabilities calculated from the transition count matrix from Table 1. It presents the likelihood of transitioning between drought, normal and wet conditions over 11 years (2011 to 2021), based on a Markov chain model. The rows represent the current state, Drought, Normal or Wet, while the columns indicate the probability of transitioning to each respective future state. The probability of staying in the Drought state from Drought is 0.247. It indicates that drought conditions may persist for a significant portion of the time, reflecting the concerns highlighted by World Health Organization [WHO], (2018) regarding mental health impacts and community displacement. The Local Authorities should prepare for prolonged droughts with emergency plans, such as water rationing and public awareness campaigns about conservation. The probabilities of staying in the Normal state and Wet state from the Drought state is 0.547 and 0.206, respectively. The relatively high probability suggests that, while drought conditions can persist, recovery is more likely. The local authorities can focus on implementing water conservation measures and enhancing water resource management during drought periods, resonating with Bekana’s recommendations for community engagement in water management. The probability of staying in the Drought state from the Normal state is 0.241. It is significant, hence indicating a considerable risk of reverting to drought conditions, emphasizing the need for monitoring and proactive management strategies. The probability of remaining in the Normal state and Wet state from the Normal state is 0.618 and 0.141, respectively. It suggests that normal conditions are stable, and local authorities can use this information for long-term planning, ensuring that infrastructure and resources are maintained and encouraging sustainable land use practices during normal periods to mitigate the risk of future droughts. The probabilities of remaining in the Drought state and transitioning from the Wet state to the Normal state are 0.217 and 0.566, respectively. Hence the possibility of reverting to drought from wet conditions exists, highlighting the need for balanced water management. Local authorities should implement strategies to retain moisture and manage runoff effectively to reduce the risks of reverting to drought. The probability of remaining in the Wet state is 0.217. It shows a low likelihood of a wet period persisting, indicating that the area is prone to droughts. The community can build reservoirs, tanks or ponds to store water for future use, plant drought resistance crops and use irrigation technologies to mention a few. It enhances the community’s drought management strategies, preparedness and ensure sustainable resource allocation, leading to better resilience against the impacts of drought.

4.3 Validating the Markov Chain Assumptions

4.3.1. Validating the Markov Chain Property (Memoryless Property)

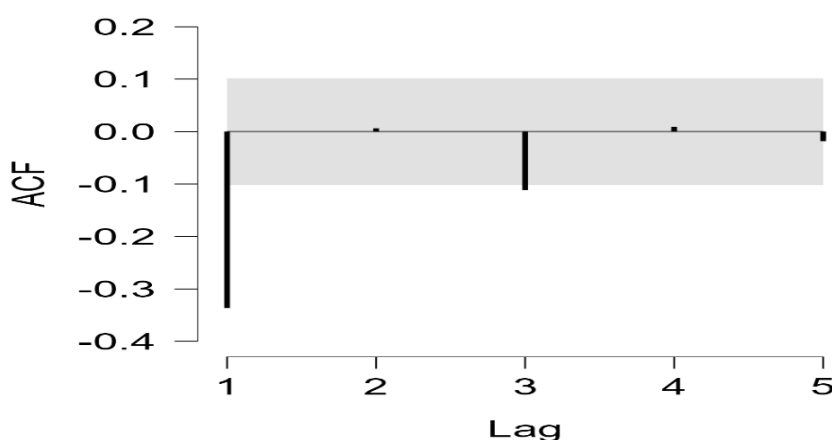


Figure 2

Autocorrelation Graph

The X-axis (Lag) represents the lag values, which indicate the time intervals at which the autocorrelation is measured. In this case, lags 1 to 5 were used. The Y-Axis (Autocorrelation Function (ACF) Values) shows the autocorrelation coefficients for each lag. Values range from -0.4 to 0.2. The shaded area around zero indicates the confidence interval (at 95%). If the ACF values fall within this interval, they are considered statistically insignificant.



Fig.2 shows that the autocorrelation at lag 1 is significantly negative as it fell outside the confidence interval. This suggests a strong negative correlation between consecutive observations, indicating that the current state is inversely related to the previous state. The autocorrelations for lags 2 and higher are near zero and within the confidence interval. This suggests that there is no significant correlation between observations that are two or more-time steps apart. The Markov property implies that the process is memoryless, meaning the next state depends only on the current state. The ACF graph indicates that while there is a dependency between consecutive states (lag 1), there is no significant dependency beyond lag 1. This pattern is consistent with a first-order Markov chain property of memoryless, where only the most recent observation influences the next state. It aligns with the theoretical framework presented by Azimi et al. (2020) who confirmed that historical data does not strongly influence current transitions after the immediate past state. This suggests that the series can be modelled as a Markov process, where the future state is primarily determined by the present state rather than past states.

4.3.2 Validating the Stationarity Assumption

It was done using the Transition Count matrix in Table 3 below:

Table 3

Transition Count Matrix

From/To	Drought	Normal	Wet	Row Total
Drought	24	53	20	97
Normal	58	149	34	241
Wet	15	39	15	69
Column Total	97	241	69	Grand Total=407

H_0 : There is no significant difference between the observed frequencies of transitions and the expected frequencies, that is, the transition probabilities between states (Drought, Normal, Wet) are stationary.

H_1 : There is a significant difference between the observed frequencies of transitions and the expected frequencies; that is, the transition probabilities are not stationary.

Sample size:407 transitions (provided a reasonable representation of the climatic states under study)

Degrees of freedom (df)= (3 rows -1) (3 columns -1) = 4

Significant Level/Critical Value is $\alpha = 0.05$

$$Chi - square Table Value = X_4^2(0.05) = 9.488$$

Decision Rule: Reject H_0 if $X_{calculated}^2 < 9.488$ otherwise, we fail to reject H_0 .

Calculating the Expected Frequencies

$$Expected Frequency = \frac{Row Total \times Column Total}{Grand Total}$$

$$24: \frac{97 \times 97}{407} = 23.12 ; 58: \frac{241 \times 97}{407} = 57.44 ; 15: \frac{69 \times 97}{407} = 16.44 ; 53: \frac{97 \times 241}{407} = 57.44 ;$$

$$149: \frac{241 \times 241}{407} = 142.71 ; 39: \frac{69 \times 241}{407} = 40.86 ; 20: \frac{97 \times 69}{407} = 16.44 ; 34: \frac{241 \times 69}{407} = 40.86$$

$$24: \frac{69 \times 69}{407} = 11.70$$

Table 4

Chi-Square Test Results

From/To	Observed (O) Frequencies	Expected (E) Frequencies	$\frac{(O - E)^2}{E}$
Drought → Drought	24	23.12	0.0335
Drought → Normal	53	57.44	0.3432
Drought → Wet	20	16.44	0.7709
Normal → Drought	58	57.44	0.0055
Normal → Normal	149	142.71	0.2772
Normal → Wet	34	40.86	1.1517
Wet → Drought	15	16.44	0.1261
Wet → Normal	39	40.86	0.0847
Wet → Wet	15	11.70	0.9308
Total	407	407	$X_{calculated}^2 = 3.724$

Since $X_{calculated}^2 = 3.724 < 9.488$ we fail to reject H_0 and conclude that the transition probabilities are stationary.

The results in Table 3 above support stationarity in the transition probability. This means that the transition probabilities among Drought, Normal and Wet states remain constant over the 11 years under study. This supports the work of Zhou et al (2022), who emphasized the importance of stable probabilities in effective drought forecasting and

management strategies. It means that the Markov chain model is valid for predicting future states based on current conditions. The Local authorities can rely on the model’s predictions for planning and resource management since its consistency allows for better forecasting and preparation for drought conditions.

4.4 Markov Chain Analysis

The analysis of the transition matrices covered the calculation of the steady-state probabilities, calculating return periods, probabilities of multiple-year droughts and the Markov chain predictions. This enables the understanding of meteorological drought persistence, recurrence and long-term behaviour.

4.4.1 Calculating the Steady-State Probabilities

Using Table 2: The Transition Probability Matrix, (P), a system of equations (Equation 1 to 4) was formed:

$$\pi_{DROUGHT} = 0.247\pi_{DROUGHT} + 0.241\pi_{NORMAL} + 0.217\pi_{WET} \quad \text{Equation [1]}$$

$$\pi_{NORMAL} = 0.547\pi_{DROUGHT} + 0.618\pi_{NORMAL} + 0.566\pi_{WET} \quad \text{Equation [2]}$$

$$\pi_{WET} = 0.206\pi_{DROUGHT} + 0.141\pi_{NORMAL} + 0.217\pi_{WET} \quad \text{Equation [3]}$$

$$\pi_{DROUGHT} + \pi_{NORMAL} + \pi_{WET} = 1 \quad \text{Equation [4]}$$

Solving the system of equations above gives the steady-state probabilities below:

$$\pi_{DROUGHT} \approx 0.23 \text{ (23\%)}$$

$$\pi_{NORMAL} \approx 0.59 \text{ (59\%)}$$

$$\pi_{WET} \approx 0.18 \text{ (18\%)}$$

The steady-state probabilities above represent the long-term equilibrium distribution of the system across the Drought, Normal and Wet states. These probabilities indicate the proportion of the time the system is expected to be in each state over the long run. The results shows that the district is expected to experience drought conditions 23% of the time, supporting the findings of Brunner et al. (2019) regarding the frequency of drought conditions in Switzerland. It indicates that drought will persist from one period to the next in the long run. Hence, the community can implement water rationing policies, developing early warning systems and enhancing community education on water conservation. The normal state is expected to prevail 59% of the time, indicating that it is the most stable condition. Local authorities can plan for infrastructure and resource management based on this predominant state. Wet conditions are less common, occurring 18% of the time. The local authorities should establish flood management and water retention strategies. This ensures that excess water during wet periods is managed effectively to prevent damage and support agriculture. These probabilities provide a framework for long-term environmental planning. Authorities can use this data to develop policies that promote sustainable water use, conservation practices and climate adaptation strategies.

4.4.2 Calculating the Return Periods (T)

The return periods were calculated as the reciprocal of the steady-state probabilities. They provide insights into how frequently different climatic states (Drought, Normal, Wet) are expected to recur. The return period, T, for the states are:

$$T_{Drought} = \frac{1}{0.23} \approx 4.35 \text{ years}$$

$$T_{Normal} = \frac{1}{0.59} \approx 1.69 \text{ years}$$

$$T_{Wet} = \frac{1}{0.18} \approx 5.56 \text{ years.}$$

The results show that drought conditions are expected to recur approximately once every 4.35 years, relating with studies by Bekana (2025) who highlighted the variability of drought occurrences. The Local Authorities can implement early warning systems and response strategies to mitigate the impacts of drought, such as public awareness campaigns, implementing efficient irrigation systems and water rationing. This relatively frequent occurrence signifies that drought management and preparedness are critical. The average return period for normal conditions is shorter, suggesting that normal weather patterns can be expected more frequently, once every 1.69 years. This highlights the stability of normal conditions, which are vital for planning and resource allocation. Wet conditions are expected to recur approximately once every 5.56 years. Although these periods are less frequent, they can have significant impacts, such as flooding or water surplus, necessitating proactive management strategies. Knowledge of return periods encourages the adoption of sustainable farming practices. Farmers can be guided to implement drought-resistant crops and efficient irrigation techniques, enhancing food security and reducing vulnerability to climate variability. Engaging the community fosters a culture of resilience and proactive behaviour in resource management and that the community responses are appropriate and effective in addressing climatic challenges.

4.5 Calculating the Probabilities of Multi-Year Droughts

We will now compute: Probability of k-year continuous droughts, Probability that a drought ends in year k and the expected length of a drought.



4.5.1 Calculating the Probabilities of k-Year Continuous Droughts

From Table 2: The Transition Probability Matrix (TPM), $P(\text{Drought}) = 0.247$.

The probability that a drought lasts for 1,2,3,4 and 5 years is given in Table 5 below.

Table 5
Probabilities of Drought Duration

Duration	Probability Formula	Value
1 year	Start in Drought	1
2 years	$P(\text{Drought})$	0.247
3 years	$P((\text{Drought})^2)$	$(0.247)^2=0.061=6.1\%$
4 years	$P((\text{Drought})^3)$	$(0.247)^3=0.0151=1.5\%$
5 years	$P(\text{Drought})^4$	$(0.247)^4=0.0037=0.37\%$

The probabilities provided in Table 5 above illustrate the likelihood of a drought lasting for consecutive years, based on the transition probability $P(\text{Drought})=0.247$. This probability represents the chance of remaining in a drought state from one year to the next. The probability of experiencing a drought for at least one year is certain (1). This serves as a baseline for understanding subsequent years. The probability of a drought lasting exactly two years in Mberengwa district is 0.247. This means that there is a 24.7% chance that if a drought starts, it will extend into the second year. The probability of a drought lasting three consecutive years is 0.061. This indicates a diminishing likelihood as the duration increases. The probability of a drought lasting four years is 0.0151 or 1.51%. This shows a further decrease in the probability of prolonged drought conditions. The probability of a drought lasting five years is 0.0037 or 0.37%. This indicates that extended droughts are quite rare. These results are consistent with the trends observed by Manyakaidze et al. (2025), who suggested that while short-term droughts are common, longer droughts are rare. Table 4 above shows that the drought persistence drops off quickly after 5 years due to a relatively low self-transition probability (0.247). The probabilities show a clear trend that, as the duration of the drought increases, the probability of it occurring decreases significantly. This reflects the increasing uncertainty and rarity of prolonged drought conditions. Understanding these probabilities is vital for local authorities in planning and resource management. Knowing that extended drought conditions are rare (0.37% chance of lasting for five years) allows policymakers to focus their efforts on shorter-term drought mitigation strategies while remaining vigilant for longer-term impacts. These probabilities provide a framework for assessing risk. Authorities can use this information to evaluate the potential impacts of drought on water resources, agriculture and community health, allowing for more informed decision-making. While longer droughts are less probable, their impact can be severe. Authorities should consider this in their long-term planning, ensuring that infrastructure and resources are adaptable to both short-term and rare, prolonged drought conditions. Hence, local authorities and policymakers can develop effective resource management strategies, prepare for emergencies, and implement sustainable practices that mitigate the impacts of drought on communities.

4.5.2 Calculating the Probabilities that a Drought Ends in year k

The probabilities calculated for a drought ending in year k were derived using the formula: (Drought ends in year k) = $P(((\text{Drought})^{k-2}) \times (1-P(\text{Drought})))$

Using results from Table 4 above we computed for k=2,3,4 and 5 years.

Table 6
Probabilities that Drought ends in year k.

Ends in year	Formula	Value
2nd year	$1-0.247=0.753$	$0.753=75.3\%$
3 rd year	$(0.247)(0.753)$	$0.186=18.6\%$
4 th year	$(0.0161)(0.753)$	$0.046=4.6\%$
5 th year	$(0.151)(0.753)$	$0.0114=1.14\%$

Table 6 above shows that if a drought begins, there's a 75.3% chance it will not last beyond the second year, reinforcing the findings of Mupepi and Matsa (2022), who identified the need for proactive measures during early drought stages. This indicates a high probability that a drought starting in the first year ends in the second year. It also shows that there is an 18.6% probability that a drought lasts exactly three years. It combines the chance of remaining in drought for two years followed by a transition to normal conditions. The probability of a drought lasting four years and then ending is 4.6%. This reflects the diminishing likelihood of prolonged droughts. The probability that a drought will last for five years and then end is 1.14%. It is low, reinforcing the rarity of such extended drought conditions. The results

highlight that the droughts (75.3%) are likely to end within the first two years. This information is crucial for local authorities as it emphasizes the need for proactive measures during the early stages of drought. As the duration of drought increases, the probability of it ending decreases significantly. This indicates that while short-term droughts are common, longer droughts are rare, which can inform risk management strategies. Knowing that most droughts are likely to end relatively quickly allows local authorities to focus their resources and response strategies accordingly. This can help in effectively managing water supplies and ensuring community preparedness. The probabilities for drought ending in years three to five, while lower, still highlight the necessity for emergency preparedness. The Local Authorities should have strategies in place for longer droughts, even if they are less likely, to mitigate potential impacts. Communicating these probabilities to the public can foster a better understanding of drought dynamics and encourage proactive water conservation practices. Awareness campaigns can focus on the importance of being prepared for both short-term and potential long-term drought scenarios. This proactive approach is vital for mitigating the impacts of climate variability on water resources and community health.

4.5.3 Calculating the Expected Length of a Drought (E(L))

The expected length of drought is derived from the probabilities of staying in drought for one year and the subsequent years. It was calculated using Table 4 results.

$$E(L) = 1 + 0.247 + 0.061 + 0.0151 + 0.0037 \approx 1.33 \text{ years} . \quad \text{Equation [5]}$$

Equation [5] shows that when a drought starts, it lasts about 1.33 years before transitioning to another state. The analysis indicates that droughts are likely to end quickly, within 1-2 years. It suggests that while droughts are a concern, they are often of shorter duration, allowing for quicker recovery. This aligns with the discussions by Javadinejad et al. (2023), who highlighted the importance of understanding the duration of drought for effective resource management and planning. Knowing the expected length of drought helps the Local Authorities to mobilise and allocate resources (like water and financial support) effectively. Farmers can also plan for drought duration by adjusting crop selection, irrigation and harvesting strategies. It provides valuable information for informed decision-making. It also enables proactive measures to reduce drought impacts on communities, agriculture and ecosystem. While the average drought lasts just over a year, authorities should still be mindful of the potential for longer droughts.

4.7 Limitations and impacts of using First Order Markov Chain Model

Using a first-order Markov chain model for predicting drought return periods has several limitations, including its memoryless property, simplicity assumptions and limited predictive power. These limitations can lead to oversimplification of complex systems, loss of valuable information and inaccurate predictions. As a result, the model may not be suitable for systems with long-term dependencies or complex dynamics, leading to inadequate planning and preparedness for droughts. To address these limitations, alternative approaches such as higher-order Markov models or machine learning techniques may be considered to capture more complex relationships and patterns in the data.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

The analysis of the Markov chain modelling of meteorological drought return periods in Mberengwa District, Zimbabwe, reveals significant insights into the dynamics of drought, normal and wet conditions from 2011 to 2021. The Transition Count Matrix revealed significant insights into climatic transitions, showing a feasibility of recovering from drought, though not guaranteed. The Transition Probability Matrix confirmed that the drought conditions may persist, but recovery is more likely, emphasising the need for proactive resource management. The validation of the Markov Chain assumptions demonstrated that the process is memoryless, supporting the applicability of the model. The analysis also confirmed the stationarity of the transition probabilities, allowing for reliable predictions of the future states. The steady-state probabilities suggest that drought conditions are expected to occur 23% of the time, with normal conditions prevailing 59% of the time and wet conditions occurring 18% of the time. Furthermore, the expected return periods for each state indicate that droughts are anticipated approximately once every 4.35 years, while normal and wet conditions recur more frequently. The findings highlight the importance of proactive resource management, particularly in preparing for potential droughts, given their recurring nature and significant impact on agriculture and water resources.

5.2 Recommendations

From the study results, the community and the policy makers are suggested to embrace the following recommendations:

Emergency Preparedness: Local Authorities should develop comprehensive emergency plans to manage drought conditions effectively, including water rationing and public awareness campaigns. *Water Conservation Strategies:* Implementing water conservation measures like efficient irrigation, rainwater harvesting, crop residue management and intercropping, during normal conditions is essential to mitigate the impact of future droughts.

Infrastructure development: Authorities should invest in infrastructure that can manage water during wet periods, including reservoirs and efficient irrigation systems. *Community Engagement:* Educating the public about drought dynamics and encouraging sustainable practices can enhance community resilience. *Monitoring and Evaluation:* Continuous monitoring of climatic conditions and regular reassessment of the Markov Chain mode will aid in more accurate predictions and timely interventions. *Adaptive management:* Policies should be adaptable to changing climatic conditions, ensuring that resources are allocated efficiently based on the current state of the environment.

REFERENCES

- Ayugi, B., Eresanya, E. O., Onyango, A. O., Ogou, F. K., Okoro, E. C., Okoye, C. O., Anoruo, C. M., Dike, V. N., Ashiru, O. R., Daramola, M. T., Mumo, R., & Ongoma, V. (2022). Review of Meteorological Drought in Africa: Historical Trends, Impacts, Mitigation Measures, and Prospects. *Pure and applied geophysics*, 179(4), 1365–1386. <https://doi.org/10.1007/s00024-022-02988-z>
- Azimi, S., Hassannayebi, E., Boroun, M., & Tahmoures, M. (2020). Probabilistic analysis of long-term climate drought using steady-state Markov chain approach. *Water Resources Management*, 34, 4703-4724.
- Bekana, T. H. (2025). Drought risk management in Ethiopia: A systematic review. *Journal of Energy, Environmental & Chemical Engineering*, 10(1), 1-11.
- Brunner, M. I., Liechti, K., & Zappa, M. (2019). Extremeness of recent drought events in Switzerland: dependence on variable and return period choice. *Natural Hazards and Earth System Sciences*, 19(10), 2311-2323.
- Dalezios, N. R., Dunkel, Z., & Eslamian, S. (2017). Meteorological drought indices: definitions. In *Handbook of drought and water scarcity* (pp. 27-44). CRC Press.
- FAO (2017). The impact of drought on agriculture: <https://www.fao.org/land-water/water/drought/droughtandag/en/>
- Hagenlocher, M.; Meza, I.; Anderson, C.C.; Min, A.; Renaud, F.G.; Walz, Y.; Siebert, S.; Sebesvari, Z. (2019). Drought vulnerability and risk assessments: State of the art, persistent gaps, and research agenda. *Environ. Res. Lett.*, 14, 1–13. <https://www.cdc.gov>
- Javadinejad, S., Dara, R., Krause, S., Riyahi, M., Mohammadi, A., & Nasserli, M. (2023). Analysis and forecasting drought characterisation with using Markov chain model. *Safety in Extreme Environments*, 5(3), 149-159.
- Kubicz, J. (2018). The application of Standardized Precipitation Index (SPI) to monitor drought in surface and groundwaters. In *E3S Web of Conferences* (Vol. 44, p. 00082). EDP Sciences.
- Kwami, T., Chigonda, T., & Rusena, T. (2018). Climate change adaptation by Farmers in Chingechuru Ward, Mberengwa District, Zimbabwe. *European Journal of Social Sciences Studies* 3(2),158-167.
- Mahmoudi, P., Ghaemi, A., Rigi, A., & Amir Jahanshahi, S. M. (2021). Recommendations for modifying the Standardized Precipitation Index (SPI) for drought monitoring in arid and semi-arid regions. *Water resources management*, 35, 3253-3275.
- Manyakaidze, P., Musavengane, R., & Maponga, R. (2025). Rural Farmer-Managed Wetland Agroecosystems Promote Climate Resilience in Semi-Arid Savannah: Case of Nyororo Wetland, Mberengwa District, Zimbabwe. *Climate Resilience and Sustainability*, 4(1), e70011.
- Montaseri, M., Amirataee, B., & Rezaie, H. (2018). New approach in bivariate drought duration and severity analysis. *Journal of Hydrology*, 559, 166-181.
- Moyo, B., Chikodzi, D., & Manatsa, D. (2021). Impacts of Meteorological Drought on Crop Production and Food Security in Semi-Arid Zimbabwe: A Case Study of Mberengwa District. *Environmental Research Letters*, 16(2), 045023.
- Mupepi, O., & Matsa, M. M. (2022). Seasonal dynamics of agro-meteorological drought in Mberengwa and Zvishavane districts between 2017 and 2020, Zimbabwe. *Natural Hazards*, 113(1), 157-184.
- Muzerengi, F., Gandidzanwa, C. P., & Chirubvu, L. (2023). Impacts of climate change on household food security in Matande communal lands, Mwenzezi district in Zimbabwe. *Jãmbá: Journal of Disaster Risk Studies*, 15(1), 1-11.
- Paulo, A. A., & Pereira, L. S. (2007). Prediction of SPI drought class transitions using Markov chains. *Water resources management*, 21(10), 1813-1827.
- Quiring, S. M. (2009). Developing objective operational definitions for monitoring drought. *Journal of Applied Meteorology and Climatology*, 48(6), 1217-1229.
- Svoboda, M. D., & Fuchs, B. A. (2016). *Handbook of drought indicators and indices* (Vol. 2). Geneva, Switzerland: World Meteorological Organization.
- WFP. (2020). Drought and food security: <https://reliefweb.int/report/zimbabwe/food-security-situation-update-wfp-zimbabwe-september-2020>.
- WHO, (2018), drought: <https://www.who.int/health-topics/drought/#tab=tab>
- Wilhite, D.A.; Glantz, M.H. (1985). Understanding: The Drought Phenomenon: The Role of Definitions. *Water Int.*, 10, 111–120.



- Yang, W., Deng, M., Tang, J., & Jin, R. (2020). On the use of Markov chain models for drought class transition analysis while considering spatial effects. *Natural Hazards*, *103*, 2945-2959.
- Yeh, H. F., & Hsu, H. L. (2019). Using the Markov chain to analyse precipitation and groundwater drought characteristics and linkage with atmospheric circulation. *Sustainability*, *11*(6), 1817.
- Zhou, Y., Zhou, P., Jin, J., Wu, C., Cui, Y., Zhang, Y., & Tong, F. (2022). Drought identification based on Palmer drought severity index and return period analysis of drought characteristics in Huaibei Plain China. *Environmental Research*, *212*, 113163.