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Prediction of Long Dry Spells for Appropriate Cropping System in Gusau Northwestern Nigeria

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Abstract
*The objective of this study was to predict the probabilities of occurrences of long dry spells and their lengths during the planting period in rainfed farming season for future planning in Gusau and its environs North-Western Nigeria. Markov chain and probability distribution models were used to help predict in advance the longtime dry spells occurrences in the study area. Daily rainfall amount for each year was used to determine the probabilities of wet and dry days at different orders of Markov Chain. Gamma distribution was used with the help of INSTAT plus statistical package to estimate the length of dry spells in May, June and July. The early season dry spells were determined to occur usually between the first and the last decades of May. The Longest dry spells for the month of May were determined to be 26, 25 and 21 days in 2020, 2022 and 2030 respectively. Low frequencies of dry spells are to be anticipated in June with only 10 days in 2026 and July with only 12 days in 2024. The month of May from 2011 to 2020 with mean dry days of measured and predicted data were found to be 14 and 15 days respectively while coefficient of variation (CV) of 0.3, shows a stable dry spell in the coming years in May. The R between the observed and the predicted values were averagely good, mean error (ME) -1.25,-1.00 and 1.63 between the longest monthly observed and predicted dry spell were less than all the observed data. The root mean square error (**RMSE)** indicated that the month of June has the highest measure of precision 3.18, followed by the month of July4.46 and May 5.50. Since, early season rainfall is uncertain and erratic than the mid-season, early planting of moisture sensitive crop like maize in Gusau without supplementary irrigation would be highly risky*.

Keywords: Prediction, Dry spell, Markov chain, and Rainfed

1.0 INTRODUCTION

Crop production, which is vital to global food security, is being affected by climate change all over the world. However, the impact is being felt more severely in developing countries that are more impoverished. It has been predicted that over the next decades, billions of people, especially those living in developing countries, will face shortages of water, food and greater risks to health and life because of climate change. (FAO, 2013).

With a growing world population and trend towards more resource-intensive diets, pressure on land and water resources for food production will continue to increase in the coming decades.

Large parts of the world rely on rainfed agriculture for their food security especially in Africa where, 90% of the food production is from rainfed agriculture (IPCC, 2007). Generally, with low yields and a high risk of crop failure. One of the main reasons for crop failure is the occurrence of dry spells during the growing season. Key indicators are the critical dry spell duration and the probability of dry spell occurrence (Fischer et-al, 2013). It is expected that environmental thresholds and tipping points such as high temperatures, drought and floods are to become more important focus in the future research (Porter, 2014).

Climate is one of the major factors controlling agricultural productivity in rainfed farming. Changes in meteorological variables such as rising temperatures, precipitation and increase in atmospheric carbon dioxide levels affect crop production (Mtongori et al, 2015). Drought consistently decreases crop yield due to water deficiency and concurrent heat, with greater yield loss for rainfed crop such as maize which is the staple food in the study area

Currently, the Intergovernmental Panel on Climate Change (IPCC) concluded that climate has changed over the past century and the trend is anticipated to continue in the future (Seneviratne et al., 2012). Even under conservative scenarios future climate changes are likely to increase with mean temperatures of 2–4 °C globally (IPCC

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2007). This change poses drought, reduction of rainfall potential, and then loss of agricultural productions (Kumar et al. 2010; Feyssa and Gemeda,
2015).

Therefore, Nigeria is not immune to this since climate change affects every country of the World. In sub-Saharan Africa, rainfed agriculture is responsible for 90% of the food production and 80% of the population rely on it for a living (Rockstr¨om, 2000).
(Otun. 2005) verified the potentials of some precipitation effectiveness variables (PEVs) such as onset, cessation, length of rainy season and their effectiveness, that is, number of rainy days and dry spell days with their frequencies and distributions. These are presumed to give first indications of climatic extreme events over a place such as Gusau and some parts of the north-western States of Nigeria.

Oguntunde et-al (2011) analyzed rainfall trends over Nigeria using 1901 – 2002 rainfall data. From their analysis they concluded that annual rainfall has reduced significantly by 50-350mm in 64% portion of Nigeria which include Gusau. Limited number of studies in Gusau focused on the rainfall onset dates, rainfall variability, planting dates and crop yield variation due to rainfall variability, but did not attempt for long-duration prediction of long dry spells.

There are various methods for predicting the occurrence of dry spells, all based on the statistical processing of rainfall event in the past. The more simple methods identify the occurrence of dry spells of a certain length (5 days, 10 days) over a certain period (one or two months or more) at the start of the rainy season and statistically assess the chance that such dry spell materialize. The problem with this method is that the frequency of dry spells in itself does not provide the right information, as the damaging effect of a dry spell depends on rainfall received prior to the dry spell (and particularly stored within the root zone). Similarly the dry spell is defined as the interval between the ends of 7 days spell beginning with onset of effective monsoon (OEM).

Also the problems are the uncertainties associated with the rainfall characteristics during the growing season. These uncertainties include the appropriate season onset of rainfall date, length, cessation and the intervening dry spells within the season. This could be as a result of lack of proper and correct tools, models and good interpretation of the climatic behaviors from the results obtained.

The use of Statistical techniques and tools such as Markov chain and probability distribution models to help predict and understand in advance the long duration dry spells remain limited. Farmers have, also realized that local experiences and indigenous knowledge in weather forecasting are no longer sufficient to guide them for agricultural planning and decision making (IPCC R4, 2007). Among the key constraints to rainfed farming in many parts of the world are non-availability or absence of good prediction and interpretation of past accurate records of observed behaviors of some climatic parameters such as probabilities of rainfall and its amount and date of occurrence of intervening long dry-spells during some developmental stages of the crop.

The annual variation of rainfall in this region as a result of extreme events makes the planning of sowing and the selection of the crop type and variety rather difficult. Reliable prediction of rainfall characteristics is needed to determine less risky planting dates or planting methods (Mugalavai et al, 2008). This is because rainfall prediction information has the potential to reduce the impact of adverse weather events. The objective of this study is to predict the probabilities of occurrences of long dry spells and their lengths during the planting period in rainfed farming season for future planning in Gusau North-Western Nigeria.

2.0 MATERIALS AND METHODS

The research is focused on Gusau which lies at 463m above sea level on Longitude $06^0$42’ East and Latitudes $12^0$20’ North. The city has a tropical climate and is situated in some parts of Northern Guinea Savanna and Sudan Savanna ecological zones (NiMet, 2020). The climate here is classified as Aw by the Köppen-Geiger system (which is one of the most widely used climate classification systems). The Köppen climate classification divides climates into five main climate groups, with each group being divided based on seasonal precipitation and temperature patterns. In Gusau, the average annual minimum and maximum temperatures recorded in the area are 26.3 °C and 30.9^0C respectively while about 888 mm of precipitation falls annually. The peak precipitation month is in August with an average precipitation amount of 262 mm.

2.1 Markov Chains

Markov chain probability model has been recognized as a suitable model to explain the long term frequency behavior of wet or dry spells. Several authors have demonstrated its practical utility in agricultural planning for both long and short term periods. This model enables one to determine the probability of occurrence of dry and wet spells during a particular period (day, week or month). Markov Chain is generally recognized as a simple and effective description of the rainfall occurrence. It has been widely applied in the disciplines of natural science, engineering, economics and management (Liu et al., 2009). Also, Markov modelling is one of the tools that can be utilized to assist planners in assessing the rainfall patterns; frequency, duration, intensity and distribution (Tetty et al, 2017).

2.2 Rainfall Occurrence Models

A simple point estimate for the probability of occurrence of a particular sequence of wet and dry days was given by Feyerherm et al (1967) as the ratio of the number of years in which the sequence occurred to the number of years of record.

$$P_0(D_t) = \frac{No.of\ years\ that\ the\ (t)th\ day\ was\ dry}{No.of\ years\ of\ records} \quad (1)$$

In which $P_0(D_t)$ indicates the initial probability for the sequence of dry days.

Other conditional probabilities can be estimated by similar ratios. Feyerherm et al (1967) also observed that, the counting problem to obtain such estimates for t= 1, 2, 3….., 365 and moderate sizes of n (number of years of records), say n > 7, is manually unmanageable. INSTAT plus, a computer programme was used to help as a tool to compute the probabilities of rainfall for the whole days (365 days) of the year as well as predict the long-time occurrences of extreme event (Long dry spells)

2.3 Conditional Probabilities

In some places of the world, it was found that the probability ***p*** of getting rain on a particular day is dependent on whether some of the previous dates were wet or dry (Stern et al., 1980b) The 1st order Markov chain analysis deals with computation of chances of rain depending on whether a previous day was dry or wet. Equations 2 and 3 were used for first and second order of Markov chain respectively as described by Feyereherm et al, (1967).

$$P_1(W_t/W_{t-1}) = \frac{No.of\ years\ that\ t^{th}\ day\ and\ (t-1)^{st} day\ were\ wet}{No.of\ years\ that\ (t-1)^{st}\ day\ was\ wet} \quad (2)$$

In order to check whether the probability of getting rain on a particular date is dependent on the conditions of the previous two days, second order Markov chain analysis was determined and the following relations were used.

$$P_2(W_t/W_{t-1}, W_{t-2}) = \frac{No.of\ years\ that\ t^{th}, (t-1)^{st}\ and\ (t-2)^{st} day\ were\ wet}{No.of\ years\ that\ (t-1)^{st}\ and\ (t-2)^{st}\ day\ were\ wet} \quad (3)$$

Where P_1= the probability of rain if the previous date was wet.

P2 = the probability of rain if the previous two days were wet.

W_t, W_{t-1} and W_{t-2} = wet days (rainfall)

This model enables the researcher to determine the probability of occurrence of dry and wet spells during a particular period (day, week or month). Markov Chain is generally recognized as a simple and effective description of the rainfall occurrence.

2.4 The Rainfall Probability Model

The expected amount of rainfall at specified probability levels were computed by fitting rainfall data with a complete Gamma distribution. This is a special case of Pearson type III distribution and has been found to fit rainfall data closely (Idris et *al*, 2016). The density function is given as

$$g(x) = \frac{\chi^{\gamma-1} e^{-x/\beta}}{\beta^{\gamma}\Gamma(\mathrm{r})} \qquad \beta > 0 \quad (4)$$

Where x is a random variable (in this case rainfall amount). β is the scale parameter, **r** describes the shape of the distribution and Γ(r)the ordinary gamma function.

The gamma distribution function has three different types, 1-, 2- and 3-parameter gamma distributions. If the continuous random variable x fits into the probability density function (pdf) of

$$f(x) = \frac{1}{\Gamma(\alpha)} \chi^{\alpha-1} e^{-x}, \qquad x \geqslant 0 \quad (5)$$

it is said that the variable x is 1-parameter gamma distributed, with the shape parameter α. In Eq. (4), Γ(α), the incomplete gamma function, is given by

$$\Gamma(\alpha) = \int_0^{\infty} \chi^{\alpha-1} e^{-x}\, dx \quad (6)$$

The distribution function has a form of the simple exponential distribution in the case of α = 1. If x in Eq. 5 is d by $^{\alpha}/_{\beta}$ where β is the scale parameter, then the 2-parameter gamma distribution is obtained as:

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \chi^{\alpha-1} e^{-x/\beta}; \qquad x \geqslant 0 \quad (7)$$

Which returns to the 1-parameter gamma distribution for β = 1. If x is replaced by $(\chi - \gamma)/\beta$ where γ is the location parameter, then the 3-parameter gamma distribution is obtained as

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} (\chi - \gamma)^{\alpha-1} e^{-(\chi-\gamma)/\beta}; \qquad x \geqslant y \quad (8)$$

2.5 Dry Spell

The mean date of commencement of dry spell and mean duration of the dry spells were worked out for the stations under study. The average durations of wet spells was also processed and by using the Gumbel's method the probabilities for each duration of dry spell during all the periods were determined. According to this method probability (P) of occurrence of dry spell greater than or equal to'd' days was given by

$$P = 1 - e^{(-e^{1}-y)} \quad (9)$$

In which 'y' is known as reduced variant which is found to be,

$$y = ln\left[-ln\left(1-\frac{1}{T}\right)\right] \quad (10)$$

where T is the return period

The probability of occurrence of a dry spell of specific duration during the critical developmental stage (May, June and July) of crops is more important from the point of view of planning of agricultural operations and protective irrigation in the case of Gusau.

3.0 DATA COLLECTION AND ANALYSIS

The time sequenced rainfall data used in this study were obtained from the Nigerian Meteorological Agency (NiMet) for the period 1981 – 2018 for Gusau. The daily rainfall amount for each year was used to determine the probabilities of rain at different levels (orders of Markov Chain). Gamma probability distribution was used to estimate the rainfall amount at different order of Markov Chain. The results obtained were subjected to statistical analysis to compare their accuracy. The data were obtained, and an assessment of data quality based on hydrological and statistical procedures performed. Then at least (30-35) years up to 2010 data were selected for this work. The remaining 8 – 10 years (2011 – 2018) data were used for testing the models.

3.1 The Length of Dry Spells

The number of years under study was simply transformed into spell length using the INSTAT plus and the longest dry spells for May, June and July, for the future years were determined. Spell lengths for crop period were also considered in order to determine the risk of having dry spells of more than 8 and 11 days after sowing.

3.2 Statistical Analysis

$$S_d = \sqrt{\left[\frac{1}{N-1}\right]\sum_{i=1}^{N}\left(d-\bar{d}\right)^2} \quad (11)$$

S_d = Standard deviation
$\bar{d}$ = sample mean
N = number of values in the sample
d = each value

3.2.1 Coefficient of Determination ***(R^2):*** measures the contribution of the linear function of k independent variables to the variation in *Y*. It is usually expressed in percentage. Its square root, *R* is referred to as the *multiple correlation coefficients.* The higher the R^2 the more accurate the forecasted values are from the observations (Efren, n.d). It ranges from 0 to 1, $R^2$of 1 indicates that the model predictions are as accurate as the mean of the observation data, whereas R^2 less than zero occurs when the observation mean is a better predictor than the model. Essentially, the closer the model efficiency is to 1, the more accurate is the model $0 \le R^2 \le 1$ (Nash and Sutcliffe, 1970).

$$R^2 = 1 - \frac{\sum_1^N ({\tau_1}^1 - \tau_m)^2}{\sum_1^N ({\tau_1}^1 - \tau_m)^2} \quad (12)$$

Where: τ_1 = predicted values
${\tau_1}^1$ = measured values
τ_m = means of measured
N = number of observations

Root mean square error (RMSE): The root mean square error is a measure of precision. If RMSE tends to zero, the measure of precision between the predicted and observed values increases (Idris, 2011).

$$RMSE = \sqrt{\left(\frac{1}{N}\left(\sum_{i=1}^{N}({\tau_1}^1 - \tau_1)\right)\right)^2} \quad (13)$$

3.2.2 Mean Error (ME): is a measure of how closely the model predicts to the field measured values. If the average value of the estimator is less than the population parameter, the bias is negative. If the average value of the estimator is greater than the population parameter, the bias is positive and the estimator is said to be positively biased (Idris, 2016). An estimator has high accuracy if it is unbiased or has a very small bias. An estimator has low accuracy if it has very large bias (Idris, 2011).

$$ME = \frac{1}{N}\sum_{i=1}^{N}({\tau_1}^1 - \tau_1) \quad (14)$$

3.2.3 Coefficient of Residual Mass (CRM): is an indicator of the tendency of the model to either over or under predict measured values. A positive value of CRM indicates a tendency of under estimation while a negative value indicates a tendency of overestimation (Idris, 2011).

$$CRM = \frac{\sum_{i=1}^{N}{\tau_1}^1 - \sum_{i=1}^{N}\tau_1}{\sum_{i=1}^{N}\tau_1} \quad (15)$$

4.0 RESULTS AND DISCUSSIONS

4. 1 Overall Probability of Rain

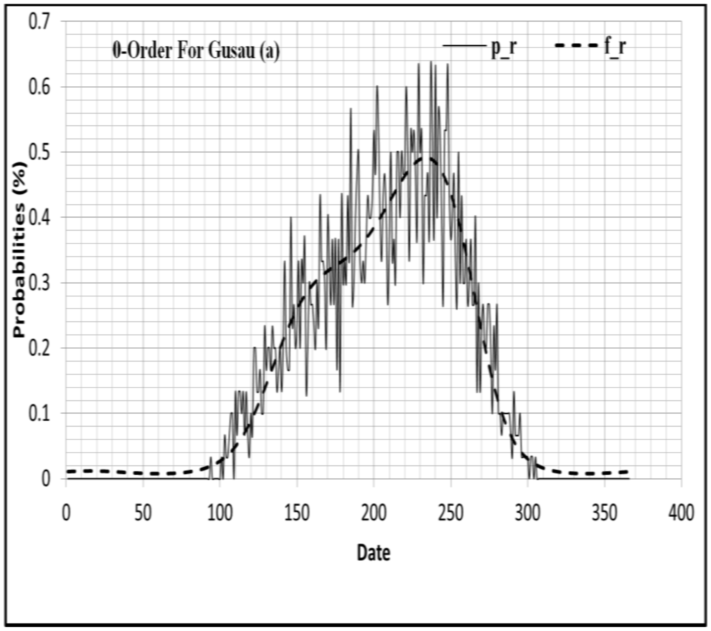

Figure 1: Observed or actual (__ p_r) and fitted (- - f_r) probabilities (0-order Markov chain), the fitted curve is a second order Fourier series with two sine, two cosine and constant terms

Figure 1 shows that the overall probability of rain at the pre-rainy season was low with probabilities < 0.16 from day 122 and below which is equivalent to 1st May and this increased to values ranging from 0.45-0.70 less accurate it could not progress to 1.0 probability around the main rainy season (June to September). This is a true representation of rainfall pattern in Gusau North Western region of Nigeria. Generally, the curve indicates that the chance of getting rain in the main rainy season is about twice as compared to the period of pre-rainy season which is true based on the characteristics of rainfall in the region.

Such information is used for crop water balance calculations to plan the agricultural system, and assess the possible length of the rain fed cropping season. The information can be used for longer-term, infrastructural, measures like land-layout for erosion control and soil conservation, intercropping systems, and contour-ridging for the conservation and use of water. Similar information is also needed for water harvesting, reservoir management and protection of land to prevent erosion hazard and the study of relationship in catchment management. After the month of June, probabilities increased to higher values greater than 0.45, an indication of higher chances of rainfall occurrences during the rainy season. Another trend of the low probabilities < 0.45 was observed from day 264 (mid-September) which indicate the beginning of post rainy season until day 303 (October ending) with almost probabilities < 0.16 which indicates a dry season. The rainy season was divided into four divisions based on the probability of occurrence of rainfall. The divisions were in such a way that dry season with (probabilities < 0.16), pre-rainy or post-rainy season (probabilities from 0.16 to 0.45) and rainy season (probabilities from 0.45 to 1), Idris; (2011).

4.2 Conditional probabilities

In some places across the world, it was found that the probability of getting rain on a particular date is dependent on whether some of the previous dates were wet or dry (Idris, 2016). The 1st-order Markov chain analysis deals with computation of chances of rain depending on whether the previous date was dry or wet. Figure 2 show the conditional probabilities of rain in the study locations

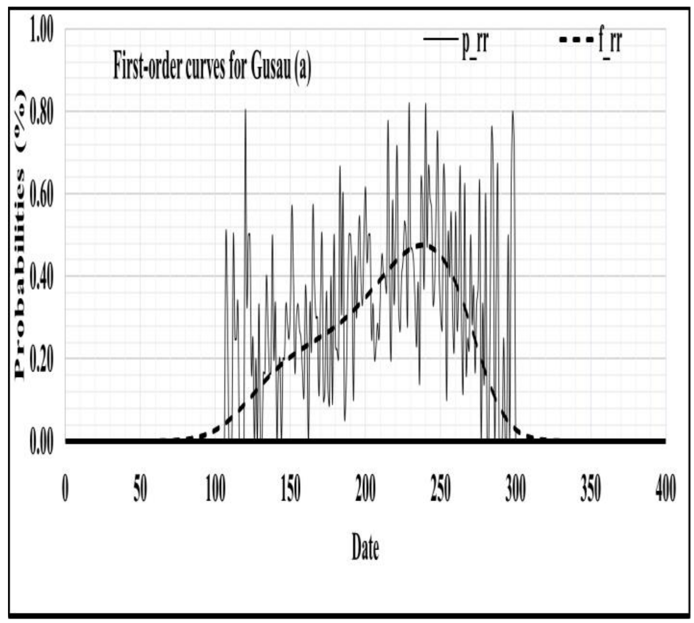

Figure 2: Actual probabilities of rain fall given the previous day rainy p_rd and the fitted probabilities (f_rr) (first-order Markov chain)

From Figure 2, the first-order Markov chain probabilities of rainfall with the condition that the previous day was either wet was plotted as (p_rr) while the smooth curves represents the fitted probability curves for the location as (f_rr). In Gusau the first-order probabilities of rain given the previous day being wet were higher ranging from 0.5 to 0.8 in the pre-rainy season which is an overestimation on the 120th day of the year equivalent to end of April, while from Fig.1, the probabilities' estimate with 0-order Markov chain on the same pre-rainy season (April) gave probabilities ranging from 0.04 to 0.2. This implies that first-order Markov chain probabilities of rain given that the previous day was wet does not fit the pre-rainy season in Gusau.

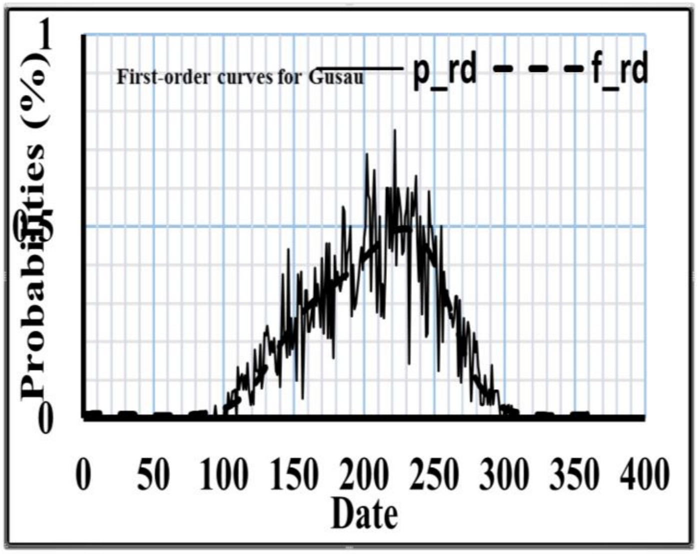

Figure 3: Actual probabilities of rain fall given the previous day dry p_rd and the fitted probabilities (f_rd) (first-order Markov chain)

Unlike the probabilities of rain given the previous day dry, Figure 2 gives low probabilities of less than 0.20 during the pre-rainy season around April ending. Probabilities >0.45 were obtained (beginning of rainy season) from 173rd day of the year upward which is in the third decade of June.

4.3 Predicted length of dry spell

The Longest dry spell lengths for 2011 to 2030 were predicted using the INSTAT plus for May, June and July, results are presented in figure 4 the results indicated that long dry spells ranging from 10 days to 27 days in Gusau were predicted in the future for the month of May. This is because in North Western Nigeria the rainy season begins within the range of these months.

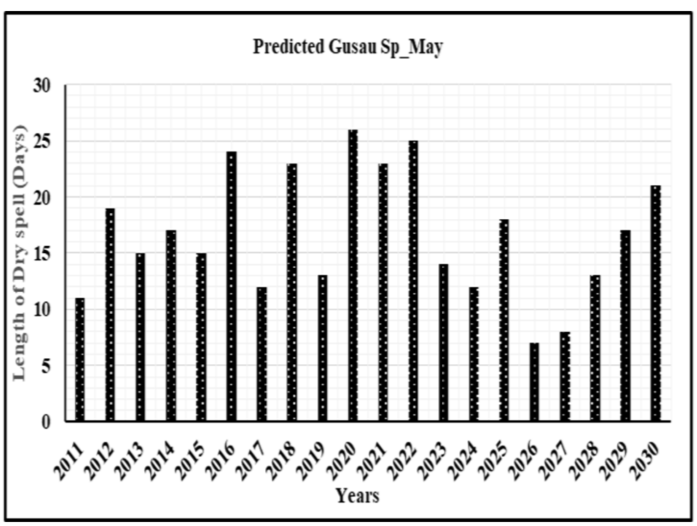

Figure 4 Predicted length of dry spells up to 2030 for Gusau in May.

Early season dry spells usually occur between the first and the last decades of May while mid-season dry spells occur around June and July. These periods of occurrences make the planting date dynamic, which apparently indicates the effect of climatic change in the region. Early season dry spells affect soil water retention which would negatively impact on crop germination and establishment while the mid-season dry spells effect is more pronounced on late maturing crop varieties.

From Gusau as shown in Figure 4, the longest dry spell occurs in May with the number of days more than 15, so planting at this time may likely be difficult especially for maize crop as the major rain fed crop in the region due to the fact that the rainfall at this time may not be equal to or exceed the potential evapotranspiration. Figure 4 also shows that in the year 2018 dry spell of 23 days occured in this study which is in disagreement with the value of 9days stated by NiMet, (2018) while in the year 2020 dry spell in May could be up to 26 days which is the highest within the range of the period under consideration. However, in 2026 the lowest dry spell in May of 7 days may be experienced which implies that there may be higher rainfall as such flood may occur. Finally it is predicted that 21 days of dry spell may occur in 2030. Thus planting in May can only be done in Gusau safely with the support of supplementary irrigation.

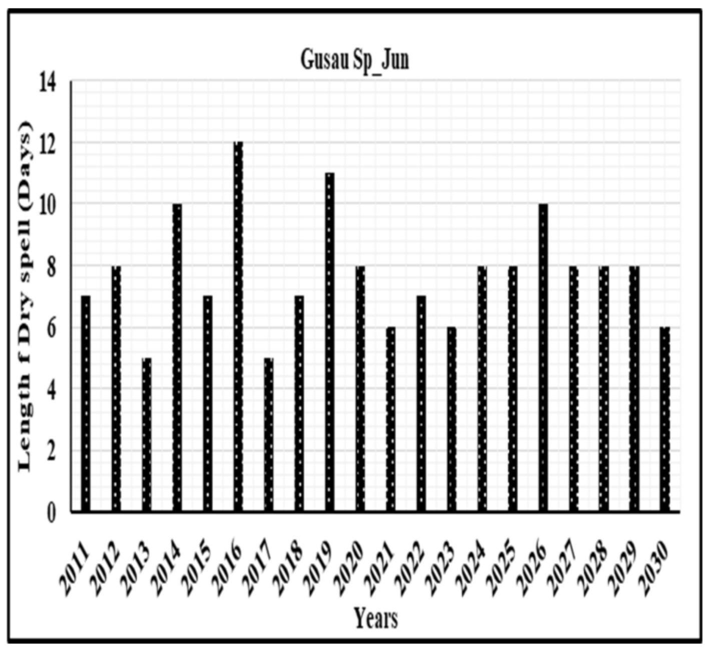

Figure 5: Predicted length of dry spells up to 2030 for Gusau in June

The month of June can be considered as beginning of the planting season in Gusau because of low frequency of dry spells. Fig 5 shows that dry spells of more than 10 days occurred in the years 2016 and 2019. This is consistent with NiMet (2019) which predicted length of dry spell in June to be above 10days in Gusau, followed by a year of less than 10 days dry spells in June. This contradicts NiMet's (2020) prediction of between 10 to 18 days in June 2020. Thus, it will be more convenient for a farmer to plant his seeds on the said planting date.

Dry spells sometimes occur in the month of July in this region, therefore, it is equally important to consider the spell lengths of July to help in planning for supplementary irrigation, fertilizer application, and insect pest sprays as well as drying some early maturing crops. From Fig 6, 2011 to 2019 dry spells were less than 10 days in July, but the predicted spell lengths dry spell of 10 days and above are to be expected in the years 2022 and 2024 respectively. This may not result in crop failure during the mid-season in Gusau, which is likely to experience excess rainfall.

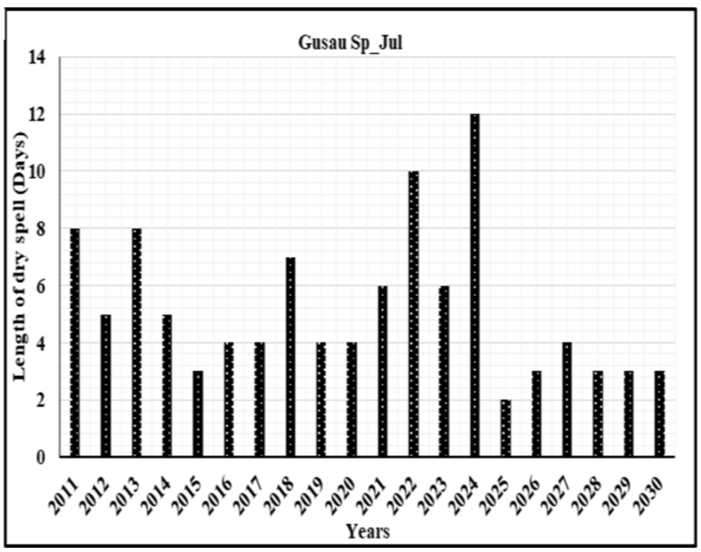

Figure 6: Predicted length of dry spells up to 2030 for Gusau

Planning of agricultural operations and water management requires the knowledge of probability of occurrences of dry spells during the rainy season for successful rainfed farming. Some of the factors that requires this knowledge for the success of rainfed farming are described below.

Planting dates requires the critical knowledge of dry spell. This is because land preparation and sowing is done within the range of these months May/June/July. Thus, trigger for land preparation and proper germination of seed and continues supply of required moisture in the soil for at least the first 30 days after planting to balance for evapotranspiration losses. Lack of good knowledge of dry spells length during the early and mid-seasons may cause very low productivity and crop failure.

From table 2, the mean dry days for the observed and the predicted data were closer to each other with only one day difference for the Month of May; similarly, the same in the month of June was observed having the mean date to be 7 days and predicted having 8 days which does not exceeds the risk limit for sowing. The range of spells length in May was 9 to 30 days which will not be suitable for sowing in May. while measure of the coefficient of variation that occur in the measured dry spell of Gusau monthly rain fall data from May to July indicates an increasingly unstable climate condition had occurred from 2011 to 2018, largely due to high CV greater than 0.4 as a results of climate change, but the month of May with CV of 0.37 shows a stable dry spell in this period and was the one with the highest frequency of dry spell. Therefore, planting is not advisable in the month of May in Gusau due to the stability of higher frequency of long dry spell.

5.0 STATISTICAL ANALYSIS

Table 1: Summary statistics for dry days in the Months

Years	**MayM**	**MayP**	**Years**	**June M**	**June P**	**Years**	**JulyM**	**JulyP**
Mean	14	15.25	**Mean**	7.25	8.25	mean	5.75	4.13
SD	6.97	5.60	**SD**	3.99	4.59	SD	2.82	2.17
MAX	30	24	**MAX**	16	17	max	12	9
MIN	9	5	**MIN**	3	3	min	3	2

MayM=May Measured, MayP=May Predicted, JuneM=June Measured, JuneP=June Predicted, JulM=July Measured, JulyP=July Predicted

Table 2: Summary statistics for the observed and predicted dry days

Variable	N	Mean	Max	Min	SD	CV
May M	8.00	14	30	9	6.97	0.50
May P	8.00	15	24	5	5.60	0.37
June M	8.00	7	16	3	3.99	0.55
June P	8.00	8	17	3	4.59	0.56
July M	8.00	6	12	3	2.82	0.49
July P	8.00	4	9	2	2.17	0.53

Table 3 Statistical Performance indicators for measured and predicted data.

Variable	R^2	R	ME	CRM	RMSE
May M May P	0.36	0.60	-1.25	-0.09	5.50
June M June P	0.35	0.59	-1.00	-0.14	3.81
July M July P	0.34	0.58	1.63	0.28	4.46

May, June and July M = Observed data, May, June and July P = Predicted data,

From table 3, it can be seen that from the model predictions, the month of May has the highest R^2 and R values followed by the month of June and July. The coefficient of determination (R^2) indicates that the accuracy of the model to predict dry spell in Gusau for monthly basis is low and the correlation relationship (R) between the observed and the predicted values were averagely good. This implies that from the coefficient of determination and correlation relationship, the model is fit to predict longest monthly dry spell of the study area with average correlation between the observed and the predicted data for the given time series.

The mean errors (ME) between the longest monthly observed and predicted dry spell periods in the study area are less than all the observed monthly values of the dry spell, this makes all the predicted values to have high accuracy.

From the Coefficient of residual mass (CRM), the model prediction of the longest monthly observed dry spell of the study area, indicate a tendency of slightly overestimation of the predicted values from the observed values, except for the month of July which indicate a tendency of underestimation of the predicted values from the observe values by 0.09 and 0.28 for the months of May and July respectively while underestimates for the Month of June by 0.14 which is a good estimate.

The result of the RMSE indicated that the month of June has the highest measure of precision followed by the month of July and May, the model accurately predicts monthly dry spell for the month of June which is the appropriate planting period in Gusau and the most critical period for the farmer to benefit from this work, than in the month of July and May.

6.0 CONCLUSION

Since, early season rainfall is uncertain and erratic than the mid-season, early planting of moisture sensitive crops like maize in Gusau without supplementary irrigation would be highly risky. This study found out the chances of occurrences of long dry spells at the early season in the month of May is very high, therefore it is not advisable to start planting moisture sensitive crops like maize. It is recommended to start planting at the end of first decade of June.

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