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A Spatiotemporal Characterization of Historical Drought Using Reanalysis Precipitation: A Useful Tool in Weather Index-Based Insurance

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Abstract

The study attempts to depict and characterize drought hazards using the reanalysis Standardized Precipitation Index (r-SPI). Also, examined is the potential of r-SPI model-based designed conceptual framework in a weather insurance contract. Due to paucity of station in-situ data, 36 years of reanalysis of precipitation data have been used to investigate the spatiotemporal characteristics of drought and its usefulness to farmers averse to risks. With fixed subjective threshold of -1.50, results revealed 4 to 11 cases of severe drought intensities of varying duration of 2 – 7 months or more. However, with varying objective thresholds of -1.33, -1.35. -1.35 and -1.33 for the Upper Niger, Inland Delta, Middle Niger, and Lower Niger sub-basins respectively, there were 4 to 13 severe drought incidences of varying duration of 2 – 7 months or more identified with the historic drought-induced famine of 1980s well captured. Every 10 years, different parts of the Niger basin experience drought events of different durations and magnitudes; with the same amount of monthly precipitation producing different SPI values and cumulative probabilities, and varying crop yields in different parts of the basin. With a conceptual framework driven by SPI 3-month, 83-88% of the variances in cereal crop yield can be explained.

Keywords: Drought, reanalysis precipitation, reanalysis-SPI, weather insurance contract, drought rose

1.0 Introduction

Widespread agricultural failure including famine, and threats to future water demand, food security, and regional economies are usually attributable to drought. For instance, it was estimated that in the twentieth century, approximately 1.9 billion people would be affected by drought (Sheffield et al., 2012). Therefore, understanding the spatiotemporal characteristics of historical droughts of a place is vital to effectively mitigate the risk of the future hazard. The assessment of historical drought events over a place and their spatiotemporal characteristics remains a major source of basic information for identifying potentials for future occurrences of drought, and the first consideration in such assessment of drought climatology is the quantification of the drought severity (Kim et al., 2011). Both the temporal and spatial dimensions of drought, usually, affect its characteristics such as onset, severity, frequency, and duration, as well as being problematic to drought index generation (Akinremi et al., 1996). According to Vicente-Serrano et al. (2012), a detailed analysis of historical drought events provides an understanding, which creates enormous possibilities for better drought management, planning, and impacts mitigation.

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This is because historical drought analysis provides vital information on deficits, such as in crop water demand, which is critical in terms of drought risk reduction (Masih et al., 2014). Such information provided through historical drought analysis has also been found useful in drought monitoring and early warning system (Salas et al., 2005); as well as in weather index-based drought insurance programs (CCAFS-CGIAR, 2014).

Over the years many economic activities, especially agriculture has suffered and still suffering from the risk of such vagaries of weather and extreme climate like drought, especially in developing countries. This has resulted in some researchers exploring the prospect of circumventing the impacts of weather-related variability on the society through the use of weather derivatives (WD) such as weather-index-based insurance (WI) (Stoppa and Hess, 2003); through a method known as weather insurance contract (WIC). In this study, a weather insurance contract (WIC) is defined as a "weather contingent contract whose payoff will be in an amount of cash determined by future weather events. It can be triggered by an underlying weather index (Stoppa and Hess, 2003). According to Dischel and Barrieu (2002), the practice of WIC hinges on the use of objective thresholds from climatic variables such as precipitation or temperature measured at defined locations to determine insurance indemnity payouts to smallholders' farmers whenever disasters occur.

The WIC is a household innovative approach to manage weather- and climate-related risks particularly, in developing countries. Unlike Asia and East Africa, the WIC approach just recently gained acceptable recognition in few places in West Africa, such as Burkina Faso, Ghana; Mali, Niger, and Senegal (Berg et al, 2009; De Bock, 2010; Molini et al., 2010). With a weather index-based insurance scheme, any farmer in a specified geographical location, who pays an annual insurance premium, can in return receive an indemnity payout, if the weather index of the location falls below a pre-determined threshold. The approach has been found to make insurance indemnity payout much easier and quicker. It is usually, devoid of arguments and confusions typically associated with the traditional crop-based insurance (Chantarat, et al., 2007; Leblois et al., 2012; CCAFS-CGIAR, 2014). The major drawback of WIC is that it often leads to the problem of basis risk (i.e., the imperfect correlation between the weather index and individual farmer's yield thereby contradicting the insurance), especially, if the farmland is not located near to the observing rainfall station (Evkaya, 2012). An attempt will be made to overcome such obstacles in this study using spatial interpolation analysis.

In terms of applicability to link the science of SPI to practice, Evkaya, (2012) used SPI values to develop basic thresholds used in drought insurance. Hence, we argue that SPI will be a useful tool in engaging farmers in West Africa in weather insurance contracts (WIC); because weather-related hazards are insurable and do not occur every year. Thus, justifying the rationale for drought monitoring and early warning. The major drawback in practicing WIC in West Africa, no doubt may be the lack of both quality historical and real-time station weather data. This will be overcome in this study using reanalysis data as a surrogate to observed station data, due to its high spatial and temporal resolution and global coverage. Moreover, reanalysis datasets have been widely used recently, in agricultural and hydrologic applications (Zhang et al., 2016). In this study, an early warning system refers to any system of data collection and analysis, coupled with timely and reliable information dissemination that aids decision-makers at all levels to be proactive in making critical management decisions, which reduces drought impacts on the society (Okpara et al., 2017).

Other drought indices have also been employed in weather index-based insurance, such as Effective Drought Index (EDI, Byun, and Wilhite, 1999), Available Water Resource Index (AWRI, Byun and Lee, 2002), Antecedent Precipitation Index (API, Shinoda, et al. 2002), and Normalized Difference Vegetation Index (NDVI, Berg, et al., 2009; De Bock, 2010; Molini et al., 2010). However, the major drawback of these approaches is that they are not probability-based and cannot estimate drought at multiple time scales that reflect the different aspects of drought events like SPI. Also, most earlier studies focused on specific drought events, thereby, making it extremely difficult comparing the severities of current day and past drought events (Kim et al., 2011), which are vital in drought management decision-making. Thus, making drought a recurring problem with a concomitant effect on livelihood in West Africa.

Until recent basin-wide study by Okpara et al (2017) that investigated the characterization of historical drought events in the Niger River basin (NRB) using the World Meteorological Organization (WMO) recommended newly developed drought index, the standardized precipitation index (SPI), and in-situ observed precipitation data of 1950 - 2001, arguably, there has not been known documented basin-wide studies before now, on characterization of historical droughts in this region. Especially, in the recent time that covered the period 2002 to 2020 either spatially or temporally. This is due to the paucity of observational network of stations in the region. Beginning from the 1980s the hydrometeorological monitoring networks have been suffering from continual deterioration with data quality and a record length significantly affected. The percentage data gaps estimated was in the range of 13.2% - 50.5% depending on location (Okpara et al., 2020). Also, an earlier study by Zhan et al (2016), posited that drought depiction in this region is generally problematic because of the paucity of observational data, occasioned by lack of dense in-situ meteorological observatories. Considering therefore, that an accurate depiction of drought in West Africa can be hampered by lack of adequate in-situ observations and meteorological network of station (Quagraine et al., 2020); reanalysis datasets are the preferred choice data in this study. According to Quagraine et al., (2020), the reanalyzes data can represent the average rainfall patterns and seasonal cycle of the region very well.

Besides the use of drought indices, there are other methods of analyzing the spatiotemporal characteristics of drought events often employed by researchers when investigating the drought climatology of a region. Among such methods for example, are the cluster analysis used for regional divisions of drought, applied in the Iberian Peninsula (Vicente-Serrano, 2006) and Iran (Dezfuli et al. 2009). The next method is the wavelet and the power spectral method employed in the analysis of drought cycles in the United States (Diaz, 1983), South Korea (Min et al, 2003), and the Czech Republic (Bra´zdil et al., 2009). The principal component analysis method has also been used in analyzing the spatial patterns of droughts in countries like Italy (Bordi and Sutera, 2002), Sicily (Bonaccorso et al., 2003), Spain (Vicente-Serrano et al., 2004), Iberian Peninsula (Vicente-Serrano, 2006) and Iran (Raziei et al., 2009). As evidenced from literature review, only a few of these studies have tried to address the issues of location, time of occurrence, duration, and severity of the past drought events. Based on the foregoing context, this study attempts to fill the gaps occasioned by inadequate and inaccurate basin-wide drought depiction due to paucity of in-situ observation data; by characterizing the region's historical drought using reanalysis precipitation data and comparing obtained results against the previous study results from in-situ observation covering the period 1980 – 2001. The study further develops a conceptual framework linking the science of SPI to practice in terms of applicability of the knowledge of characterization of the drought climatology in the weather insurance contract (WIC). It is, therefore, important, and timely because, the capacity to deal with climate extreme and associated hazards depends principally on the extent to which the problem is understood (Van Apeldoorn, 1981). Besides there is an urgent need for the agricultural sectors in developing countries to implement appropriate adaptation and mitigation measures Kadigi et al. (2013).

2.0 Data and Method

In West Africa, precipitation data have been kept from different years in different parts of the Niger River Basin. A preliminary analysis of the status of the region's hydrometeorological monitoring station revealed continued declining trend in the precipitation networks of stations. (Fig. 1). The Niger River Basin has diverse geographical and climatic characteristics that play an important role in the water resources availability, which in turn influences a range of water resources–related activities in the basin (Olomoda, 2005). The transboundary river basin is inhabited by over 110 million people spread across 9 countries that shared the basin, namely, Benin, Burkina Faso, Cameroun, Chad, Cote d'Ivoire, Guinea, Mali, Niger, and Nigeria. Nigeria constitutes about 73% of the basin's population and occupies the biggest portion of the active basin catchment area (approx. 39%). Based on its peculiar topographic, hydro-climatic, and drainage characteristics, the entire Niger basin is usually sub-divided into four watersheds as shown in Fig. 2, with homogenous physical and geographical characteristics (World Bank, 2005; Mahe et al., 2009). This is with the view to effectively understand the river discharge characteristics, for ease of analysis, interpretation, and decision-making. The four watersheds are the Upper Niger Basin; the Inland Delta; the Middle Niger Basin; and the Lower Niger Basin.

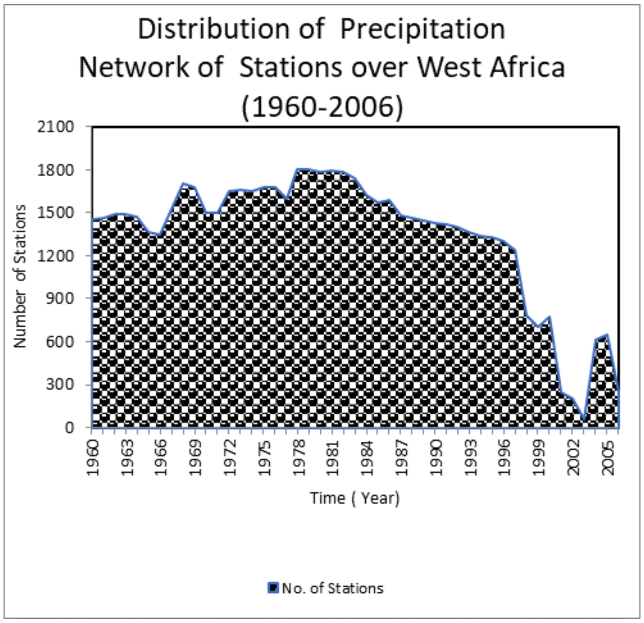

Fig. 1: Deteriorating trend of precipitation network of station over West Africa

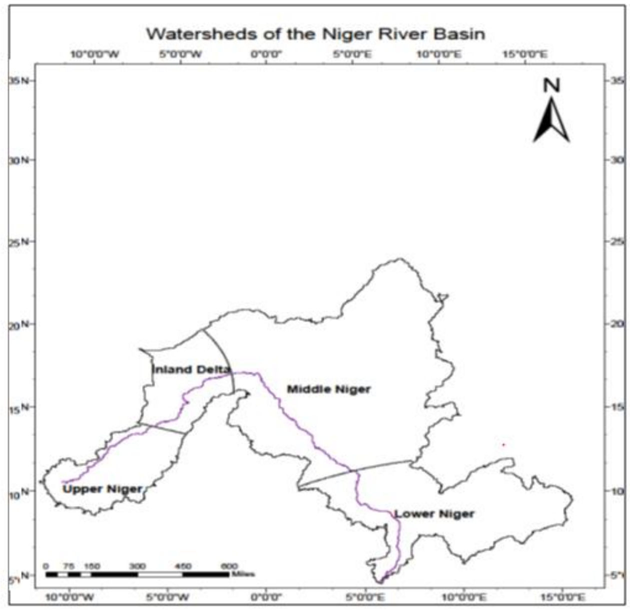

Fig. 2: The Four watersheds of the Niger River Basin West Africa (Source: Okpara et al.,2017)

The analysis in this study is based on monthly reanalysis precipitation records (1980 – 2016) with a spatial resolution of 0.25° × 0.25° extracted over 60 locations across the basin (Fig.3) from the Princeton University, African Water Cycle Monitor (AWCM) database http://stream.princeton.edu/AWCM/WEBPAGE/interface.php). The dataset was preferred because (1) paucity of observational data remains a major problem to depiction of drought in the continent (Zhan et al., 2016); especially, there is a lack of dense in-situ hydro-meteorological data network in the region, (2) the database provides hydro-meteorological series of high resolution and quality covering the extensive period 1950 - present. Besides, it is a robust and stable system that provides consistent and continuous hydro-meteorological data. It is developed by Princeton University in collaboration with UNESCO, for operational and research use over Africa. It has been widely used in hydro-meteorological and agricultural applications. According to the European Community Medium Weather Forecast (ECMWF), climate reanalysis refers to the numerical description of the recent climate of a place produced by combining models with observations.

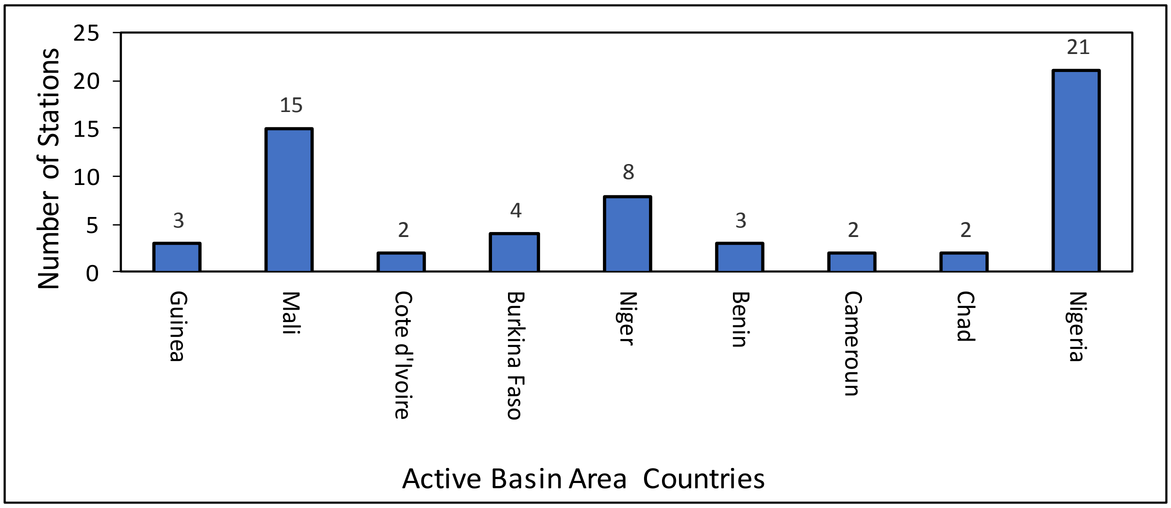

Fig. 3: Country-wise distribution of number of stations in the study area

Normally, they are products of a single model version and data assimilation method, which consists of estimates of atmospheric parameters such as air temperature, pressure, and wind at different altitudes, and surface parameters such as rainfall, soil moisture content, and sea-surface temperature. Such estimates are often produced for all locations on earth, and usually span a long period that can extend back by decades or more (https://www.ecmwf.int/en/research/climate-reanalysis). Other datasets used include crop yields(cereal), digital elevation model (DEM), etc.

Conceptually, the standardized precipitation index (SPI) was developed with the understanding that precipitation deficits are the major carrier of drought signals Changnon (1987), which can be propagated through the hydrologic system resulting in the deficits of soil moisture, streamflow, groundwater, reservoir storage, etc. By implication, SPI has been designed to quantify precipitation deficits on multiple time scales; reflecting the cascading nature of drought through the hydrologic system and its concomitant impacts on different water resources occurring at different time scales (McKee et al.,1993). The SPI is a percentile- or probability-based drought index whose unit of measurement is in standard deviation. Thus, it normally calculates the number of standard deviations at which the observed cumulative rainfall at a given time scale deviates from the long-term mean. The approach involves a normalization process, which allows for the prediction of both dry and wet seasons over a specific period. The computation of SPI at a shorter timescale usually reflects meteorological and agricultural droughts, while the longer timescale reflects a hydrological drought (Heim, 2002). Based on an earlier study by Okpara et al. (2017), two (2) parameters Gamma distribution fits the precipitation distribution in the Niger basin better than other distributions. Thus, gamma distribution has been used in the computation SPI in this study. Precipitation time series often exhibit strong non-stationarity over West Africa (Tarhule et al., 2014), resulting in precipitation being skewed at finer timescales of months and weeks; it is necessary, therefore, to calculate the SPI, the time series is first converted to standard normal through equiprobability transformation (WMO, 2000).

Equiprobability is a concept that allows one to assign equal probability values to outcomes when they are judged to be equipossible or to be equally likely to occur in some sense (Panofsky and Brier, 1958; Wilhite, 2005). This, therefore, implies that equiprobability transformation allows the SPI to determine rainfall amount and its probability of occurrence and required amount of rainfall to end a prevailing drought event (Blain, 2012). The computation of SPI involves three main steps (i) selection of monthly long-term precipitation record (30 years or more) for the desired time scale, (ii) selecting the probability distribution that best describes the data and compute the probability density function (PDF) and its conversion to cumulative distribution function (CDF), and (iii) transforming the CDF into standard normal distribution. The probability density function (pdf) of the gamma distribution can be mathematically expressed as stated below (McKee et al., 1993).

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

where: $\alpha > 0$, $\beta > 0$, $x > 0$

The cumulative distribution function (G(x)) is expressed as;

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}\hat{\alpha}\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}} e^{-x/\hat{\beta}} \qquad (2)$$

$$G(x) = \frac{1}{\Gamma(\hat{\alpha})} \int_0^x \frac{x^{\hat{\alpha}}}{\beta^{\hat{\alpha}}} e^{-x/\hat{\beta}} dx \qquad (3)$$

By substituting $t = \frac{x}{\beta}$, equation 3 yields the incomplete gamma function, expressed as below:

$$G(x) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\hat{\alpha}-1} e^{-t} dt \qquad (4)$$

where

α, β, x is the shape parameter, scale parameter and precipitation amount respectively.

For $\alpha > 0$, the gamma function $\Gamma(\alpha)$ is a quantity defined by eqn. 5

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx \qquad (5)$$

where,

$\Gamma(\alpha)$ is the gamma function, x is precipitation amount.

Fitting the gamma distribution to the rainfall data requires estimating α and β. These parameters were estimated using Maximum Likelihoods (Thom (1958):

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad (6)$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \qquad (7)$$

and

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \qquad (8)$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \; for\; 0.5 < H(x) < 1.0 \qquad (9)$$

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \; for\; 0 < H(x) < 0.5 \qquad (10)$$

where α and β are the parameters of the distribution, A is the difference between the logs of arithmetic and geometric means, is the mean of the cumulative precipitation. The constants are C0 = 2.515517, C1 = 0.802853, C2 =0.010328, d1 = 1.432788, d2 = 0.189269, and d3 = 0.001308.

In this study, SPI is computed using the program code developed by the U.S. National Drought Mitigation Center (US-NDMC). The program code is freely available at http://drought.unl.edu/MonitoringTools/DownloadableSPIProgram.aspx.

Usually, the application of SPI in drought identification outside the United State where it was developed originally, is subjective and done using arbitrary thresholds (McKee et al.,1993; Acheampong, 1990); because the thresholds are used without any consideration to specific drought impact in the region being used. In this study, therefore, the subjective drought severity categories proposed by McKee et al. (1993) are being adopted as summarized in Table 1. This is with the view to ensure the obtained results from reanalysis precipitation data are comparable to the results of an earlier study carried out with in-situ observation records. Therefore, for any month and at any given location in the Niger Basin, the onset of droughts of moderate intensities can be defined or identified when SPI values are in the range of -1 to -1.49 over two or more consecutive months, which has a probability of occurrence of 15%. While drought of severe intensity is defined or identified when SPI value is in the range of -1.5 to -1.99, with an occurrence probability of 5%. Based on these selected thresholds the characterization of the drought climatology of the Niger Basin has been carried out using the runs theory, which can be mathematically expressed as below to estimate the deficit volume at time t (D(t)). By calculating the deficit volume, the severity of a drought event can be determined.

$$D(t) = \begin{matrix} \tau(t) - X(t) & for\, X(t) < \tau(t) \\ 0 & for\, X(T) \geq \tau(t) \end{matrix} \quad \ldots\ldots(11)$$

where $\tau(t)$ is the threshold, X(t) is the value of variable X, which can be precipitation, soil moisture or streamflow etc., The deficit volume for any drought event can be calculated with:

$$D_j = \sum_{S_j}^{L_j} D(t) \quad \ldots\ldots(12)$$

where j is the drought event, Sj represents the value of t at which drought event j begins, Lj is the length of the drought, and Dj is the deficit volume of the drought.

Table 1: Drought Severity Classification Scheme

SPI value	Drought Category	Cumulative Frequency (%)	Probability of occurrence (%)
< - 2.0	Extreme Drought	< 2.3	2.5 (once in 40 years)
-1.5 to -1.99	Severe Drought	2.3 - 6.8	5 (once in 20 years)
-1.0 to -1.49	Moderate Drought	6.9 - 15.9	15 (once in 6.7 years)
-0.5 to -0.99	Mild Drought	16 - 36.9	30 (once in 3 years)
-0.49 to 0.49	Normal	37 - 50	50
0.5 to 0.99	Mildly Wet	51- 70	70
1.0 to 1.49	Moderately Wet	71 - 84.1	85
1.5 to 1.99	Severely Wet	84.2 - 95	95
≥ 2.0	Extremely Wet	> 97.7	98

Like the earlier study by Okpara et al (2017), the geographical extent of drought in the study region has been analyzed using the Inverse Distance Weighting (IDW) method of spatial analyst tool of ArcGIS 10 software due to its deterministic and simplistic nature. The approach requires less computational effort and is best for quick interpolation of sparse rainfall datasets on both regular or irregular spaced samples (Legates and Willmont, 1990; Hartkamp et al., 1999). The major limitation of the approach is in the selection of the weighting function, which is subjective. Nevertheless, recent studies have shown that deterministic interpolation methods such as IDW outperform the geostatistical method such as Kriging in rainfall interpolation (Ly et al., 2013; Dirk et al., 1998). The distribution of the different drought events in the basin and their durations has been carried out through drought rose analysis.

To apply SPI in the weather index-based insurance, the authors argue that (i) where the long-term mean is used as the threshold, then, as the long-term mean changes over time, a new norm must be re-established, and (ii) the index needs to be tested for normality assumption and ensures it satisfies the assumption for the outcomes of the index insurance to be reliable or valid. Based on the above qualifications, the SPI-based Insurance (SBI) conceptual framework is being proposed in this study with the view of integrating the SPI metric into a weather index-based insurance as shown in Fig 4. To design an effective Weather Index-based Insurance, Evkaya (2012) posited that the most critical starting point is to determine how the weather index variable is correlated with the actual value of the loss (i.e., Crop yield reduction). Given that rainfall amount in Africa is usually poorly correlated with crop yields (Evkaya, 2012; Sultan et al., 2014) at annual time scale, the relationship will even be worst with finer timescales such as a month, weekly or daily, due to the presence of noise in the time series. In this study, an attempt has been made to improve the weather index and the crop yield relationship by first detrending the cereal yield and derive a time series of a Standardized Cereal Crop Index (SCCI) using the SPI approach.

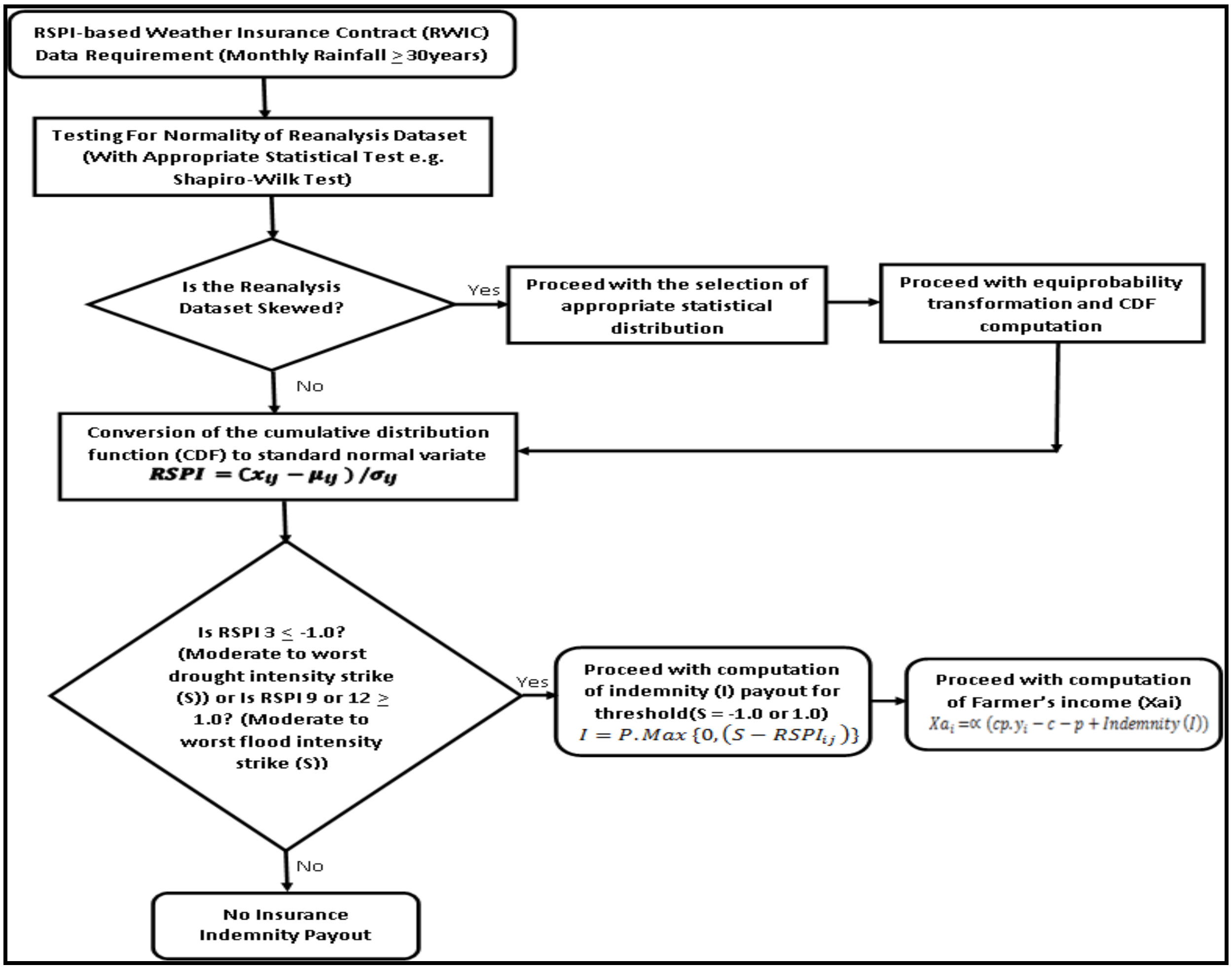

Fig. 4: The Conceptual Framework for SPI-based Weather Insurance Contract (SWIC)

3.0 Results and Discussion

As evidenced in Fig.5, the conceptual graph of the equiprobability transformation in SPI using reanalysis precipitation, the same amount of August monthly rainfall of 200mm produced different SPI values and cumulative probabilities in different parts of the basin (i.e., Upper Niger, Inland Delta, Middle Niger, and Lower sub-basins).

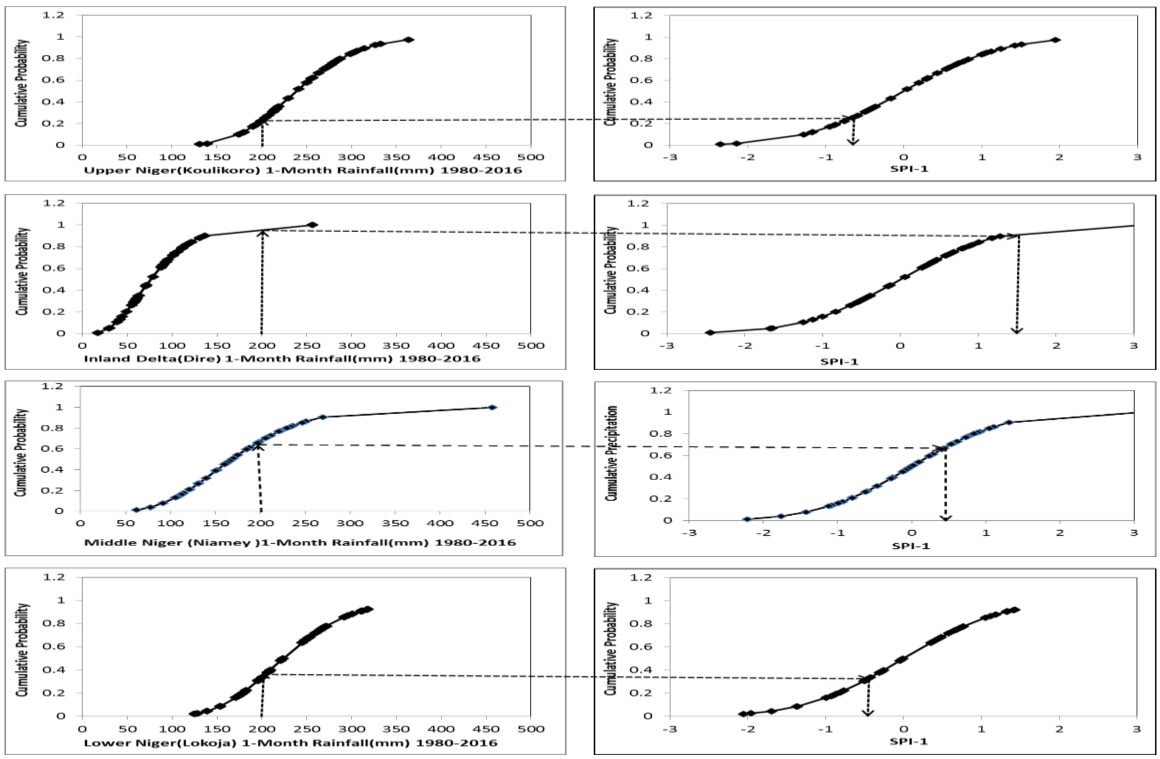

Fig. 5: Equiprobability transformation of reanalysis rainfall distribution in the Niger basin

These corresponding SPI values and the cumulative probabilities obtained for each of the sub-basins are -0.765, 2.37, 0.435, - 0.421 and 0.224, 0.960, 0.670 0.315 respectively. By implication, drought episodes at different locations of the Niger Basin are comparable in space and time. Thus, farmers in different parts of the basin will experience the effects of the same amount of rainfall differently. The findings agree with the earlier study of Okpara et al (2017) over the Niger Basin using in-situ observations; as well as the study of Guttman (1999). The onset of a drought of moderate, severe, and extreme intensities occurs when the SPI values fall below subjective thresholds of -1.0, -1.5, or less than -2 respectively, over two (2) or more consecutive months in the four respective sub-basins of the Niger Basin. However, when the SPI values hit a threshold value of 0.5 and above, recovery from drought occurs. The result agrees with the findings of Mckee et al (1993) and Okpara et al. (2017). Based on the fixed subjective threshold of -1.5 for instance, 4 to 11 occurrences of severe drought intensities of varying duration ranging from 2 – 7 months or more depending on the location were identified using the SPI 3-month (as a proxy for agricultural drought) and SPI 12-months (as a proxy for hydrological drought) at Upper Niger sub-basin in the year 1981, 1984 – 1988 and 1990 (from-situ observed data(o-SPI)) or 1982 – 1985, 1987 – 1988 and 1998 (from reanalysis data (r-SPI)). Drought of the same magnitude were identified in the Inland Delta sub-basin in 1982, 1989, 1997 and 1998(o-SPI) or 1982,1983, 1985, 1986 and 1990-1992(r-SPI); as well as in the Middle Niger sub-basin in 1982, 1984, 1985, and 1987(o-SPI)) or 1982-1985 and 1987-1988(r-SPI) and in the Lower Niger sub-basin in 1982 – 1984 and 1993(o-SPI) or 1981 -1984, 1987, 2001-2005 and 2013(r-SPI). However, with the varying objective thresholds of -1.33, -1.35. -1.35 and -1.33 for the Upper Niger, Inland Delta, Middle Niger, and Lower Niger sub-basins respectively, 4 to 13 occurrences of severe drought intensities of varying duration ranging from 2 – 7 months or more depending on the location were identified using the SPI 3- and SPI 12-months respectively. At the Upper Niger sub-basin, drought was identified in the year 1981, 1983 – 1986, 1988 and 1990 (o-SPI) or 1982 – 1985, 1987, 1988, 1993, and 1998 (r-SPI); then, in the inland Delta sub-basin it was in 1982, 1989, 1997, and 1998(o-SPI) or 1982- 1988, and 1990 – 1992 (r-SPI).

In the Middle Niger sub-basin drought was identified in the year 1981, 1982, 1984 – 1987, and 1989(o-SPI) or 1982 -1985, 1987, 1988, 1993 and 2015(r-SPI); and in the Lower Niger sub-basin it occurred in 1982 – 1984, 1993 and 1998(o-SPI) or 1981 – 1985, 1987, 2000 – 2005, and 2015(r-SPI) (Tables 2 - 9).

Table 2: Identification of severe to worst Drought over the Upper Niger Sub-basin (Koulikoro) using Subjective threshold of -1.50

Drought Duration	Observed station data			Reanalysis Data		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	May-Jun, 1986; May-jun,1990	Sept-Oct, 1981; Sept-Oct,1987; Jul - Aug, 1988	1981, 1984, 1985, 1986, 1987, 1988 and 1990	Aug-Sept,1982; Jun-Jul, 1998	Sept-Oct,1987	1982, 1983, 1984, 1985, 1987, 1988, and 1998
3-months	Jul-Sept,1984; Aug-Oct, 1985; May-Jul,1988			Jul-Sept, 1983; Aug-Oct, 1984; May-Jul, 1985	Apr-Jun, 1988	
4-months						
5-months	Jun-Oct, 1981					
≥6-months		Aug,1984 - Jul,1986		Apr-Sept, 1987	May,1983-Jul,1985	

Table 3: Identification of severe to worst drought over Upper Niger Sub-basin (Koulikoro) using objective threshold of -1.33

Drought Duration	Observed station data (1980-2001)			Reanalysis Data (1980-2001)		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	May-Jun, 1986; May-Jun, 1990	Sept-Oct, 1981; Jun-Jul, 1983	1981, 1983, 1984, 1985, 1986, 1988, and 1990	Jun-Jul, 1998		1982, 1983, 1984, 1985, 1987, 1988, 1993, and 1998
3-months	Aug-Oct, 1985; May-Jul, 1988	Jul-Sept, 1988		Aug-Oct, 1982; Jul - Sept, 1983; May-Jul, 1985; Apr-Jun, 1993;	Aug-Sept,1987; Apr-Jun,1988	
4-months	Jul-Oct, 1984			Jul-Oct,1984;		
5-months	Jun-Oct, 1981					
≥6-months		Aug, 1984 - Jul, 1986		Apr-Sept, 1987	May,1983 - Jul,1985	

Table 4: Identification of severe to worst drought over Inland Delta Sub-basin (Dire) using subjective threshold of-1.50

Drought Duration	Observed station data			Reanalysis Data		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	Jun - Jul, 1982; Jun - Jul, 1989		1982, 1989, 1997, and 1998	Sept - Oct, 1985; Aug - Sept, 1991	Jun-Jul, 1986; Aug Sept, 1991; May-Jun, 1992	1982, 1983, 1985, 1986, 1990, 1991, and 1992
3-months	Aug-Oct, 1997			Jul - Sept,1982;	Aug-Oct,1990	
4-months		Jul - Oct, 1982				
5-months						
≥6-months		Aug, 1997 - Jul, 1998			Jul, 1982 - Oct, 1983	

Table 5: Identification of severe to worst drought over the Inland Delta sub-basin (Dire) using objective threshold of -1.35

Drought Duration	Observed station data (1980-2001)			Reanalysis Data (1980-2016)		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	Jun - Jul, 1982; Jun - Jul, 1989		1982, 1989, 1997, and 1998	Sept - Oct, 1985; Aug-Sept 1991	May - Jun, 1992	1982, 1983, 1984, 1985, 1986, 1987, 1988, 1990, 1991 and 1992
3-months	Aug - Oct, 1997			Jul - Sept, 1982; Jul - Sept, 1983; Jul -sept, 1987; Aug - Oct, 1990	Jun - Aug, 1986; Aug - Oct, 1987; Apr - Jun, 1988	
4-months		Jul - Oct, 1982				
5-months						
≥6-months		Aug, 1997 - Jul, 1998			Jul, 1982 - May,1984; Aug, 1990 - Sept, 1991	

Table 6: Identification of severe to worst drought over the Middle Niger sub-basin (Niamey) using Subjective threshold of -1.50

Drought Duration	Observed station data (198-2001)			Reanalysis Data (1980 – 2016)		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	May- Jun, 1987		1982, 1984, 1985, and 1987	Aug - Sept, 1984; Sept - Oct, 1987; Apr - May, 1988		1982, 1983, 1984, 1985, 1987, and 1988
3-months	Jul - sept, 1984					
4-months				Jul - Oct 1982; May -Aug, 1987		
5-months		Jun - Oct, 1982				
≥6-months		Jul 1984 - Jul, 1985			Jul, 1982 - Apr, 1983; Aug, 1984 - Jul, 1985	

Table 7: Identification of severe to worst drought over the Middle Niger Sub-basin (Niamey) using objective threshold of – 1.35.

Drought Duration	Observed station data (1980-2001)			Reanalysis Data (1980-2016)		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	Sept - Oct, 1981; Jul -Aug, 1986; May - Jun, 1989		1981, 1982, 1984, 1985, 1986, 1987, and 1989	May - Jun, 2015	Aug - Sept, 1993	1982, 1983, 1984, 1985, 1987, 1988, 1993, and 2015
3-months	Jun-Aug, 1982; Jul - Sept, 1984; May - Jul, 1987			Aug - Oct, 1984		
4-months				Jul - Oct, 1982; May -Jul, 1985; May - Aug, 1987		
5-months		Jun - Oct, 1982				
≥6-months		Jul, 1984 - Jul, 1985			Jul,1982 - May, 1983; Aug, 1984 - Aug, 1985; Sept, 1987 - May, 1988	

Table 8: Identification of severe to worst drought over Lower Niger Sub-basin (Lokoja) using subjective threshold of – 1.50

Drought Duration	Observed station data (1980 -2001)			Reanalysis Data (1980 - 2016)		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	Sept - Oct, 1983; Aug - Sept, 1993		1982, 1983, 1984 , and 1993	Apr - May,1981; Sept - Oct, 1983; Jun - Jul, 1987	Sept - Oct, 1983; Jun - Jul, 1984; Sept -Oct, 2005	1981, 1982, 1983, 1984, 1987, 2001, 2002, 2003, 2004, 2005 and 2013
3-months				May - Jul, 2000; Aug - Oct, 2001; Aug - Oct, 2005; Aug - Oct, 2013	Apr - Jun, 2002	
4-months	Jul -Oct, 1982			May - Aug, 2003	Aug,2003 - Apr, 2004	
5-months						
≥6-months		Aug,1982 - Jul, 1984			Aug, 1982 - May, 1983	

Table 9: Identification of severe to worst drought over Lower Niger Sub-basin (Lokoja) using Objective threshold of -1.33

Drought Duration	Observed station data (1980-2001)			Reanalysis Data (1980-2016)		
	o-SPI 3	o-SPI 12	Drought Years	r-SPI 3	r-SPI 12	Drought Years
2-months	Sept - Oct, 1983; Aug - Sept, 1993; Apr - May, 1998		1982, 1983, 1984, 1993, and 1998	Apr - May, 1981; Sept - Oct, 1983; Sept - Oct, 1985; Jun - Jul, 1987; Jun -Jul, 2015	Apr - May, 1981; Sept - Oct, 1983; Jun - Jul, 1984; Sept - Oct, 2005	1981, 1982, 1983, 1984, 1985, 1987, 2000, 2001, 2002, 2003, 2004, 2005, and 2015
3-months				May - Jul, 2000, Aug - Oct, 2001; Aug - Oct, 2005; Aug - Oct, 2013	Apr - Jun, 2002	
4-months	Jul Oct, 1982					
5-months				May-Sept, 2003	Jul, 2003 - Apr,2004	
≥6-months		Aug,1982 - Jul, 1983; Sept, 1983 - Jul, 1984			Jul, 1982 - Jun, 1983	

By implication, SPI metric driven by either in-situ observed precipitation data or reanalysis precipitation data captured well the major drought events of the 1980s which extended even to the Guinea coast in the Lower Niger sub-basin. Results further revealed that every 10 years, different parts of the Niger basin experience drought events of different magnitude and duration, which concurs with the available information on drought disasters in the International Disaster Database of the Centre for Research on the Epidemiology of Disasters (EM-DAT CRED) (www.emdat.be) for diverse countries within the Niger basin.

Furthermore, the exploratory data analysis results of the temporal evolution of drought episodes based on the reanalysis precipitation data revealed short-term drought events with a higher frequency of occurrence than the long-term drought events with lower frequency in the Niger basin (see Figs. 6 – 9). Results showed 8, 7, 7, and 6 short-term drought events and 5, 3, 4, and 3 long-term drought events of moderate to extreme intensities at the Upper Niger, Inner Delta, Middle Niger, and Lower Niger sub-basins respectively. Both inter-annual and decadal variability in the temporal characteristics of the drought /flood conditions over all the sub-basins are high in frequency.

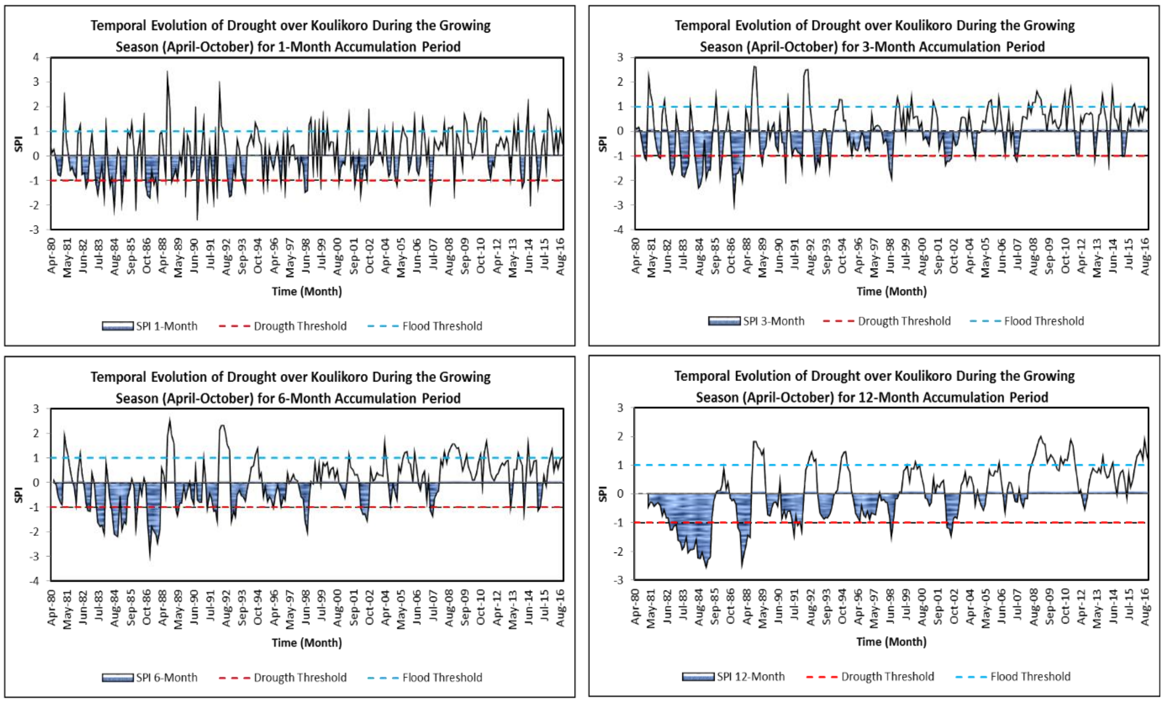

Fig. 6: Upper Niger Watershed 1-, 3-, 6-, and 12- Months SPI time series

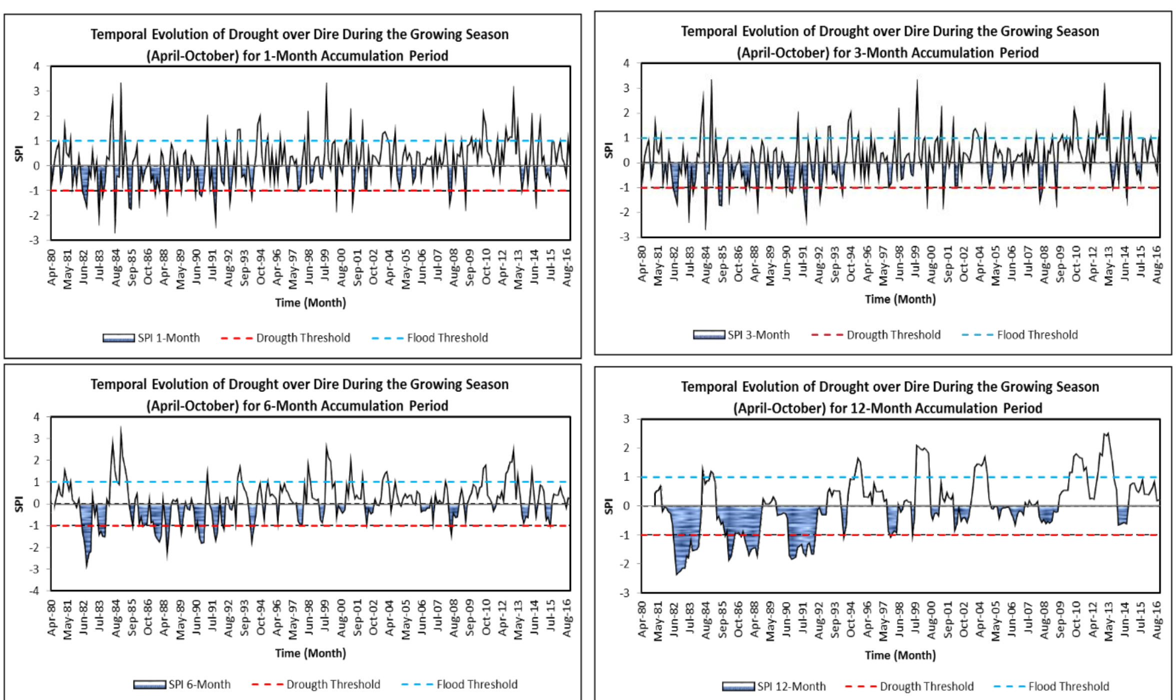

Fig. 7: Inland Delta watershed 1-, 3-, 6-, and 12- Months SPI time series

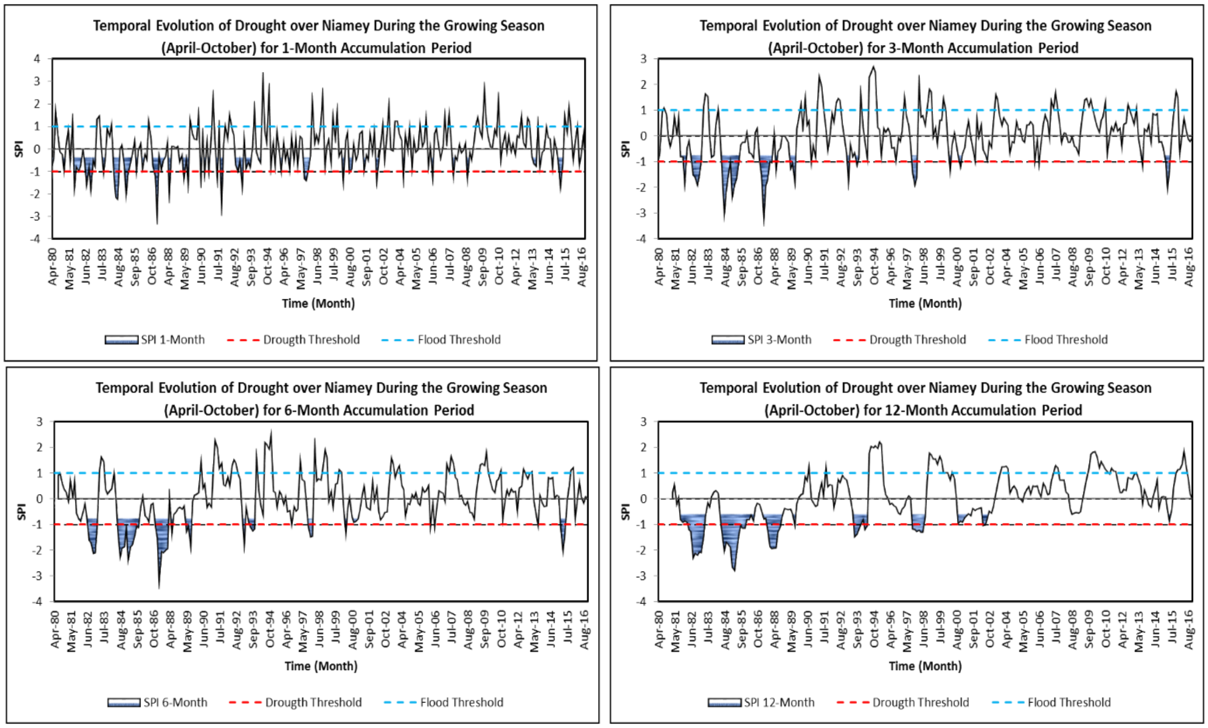

Fig. 8: Middle Niger Watershed 1-, 3-, 6-, and 12- Months SPI time series

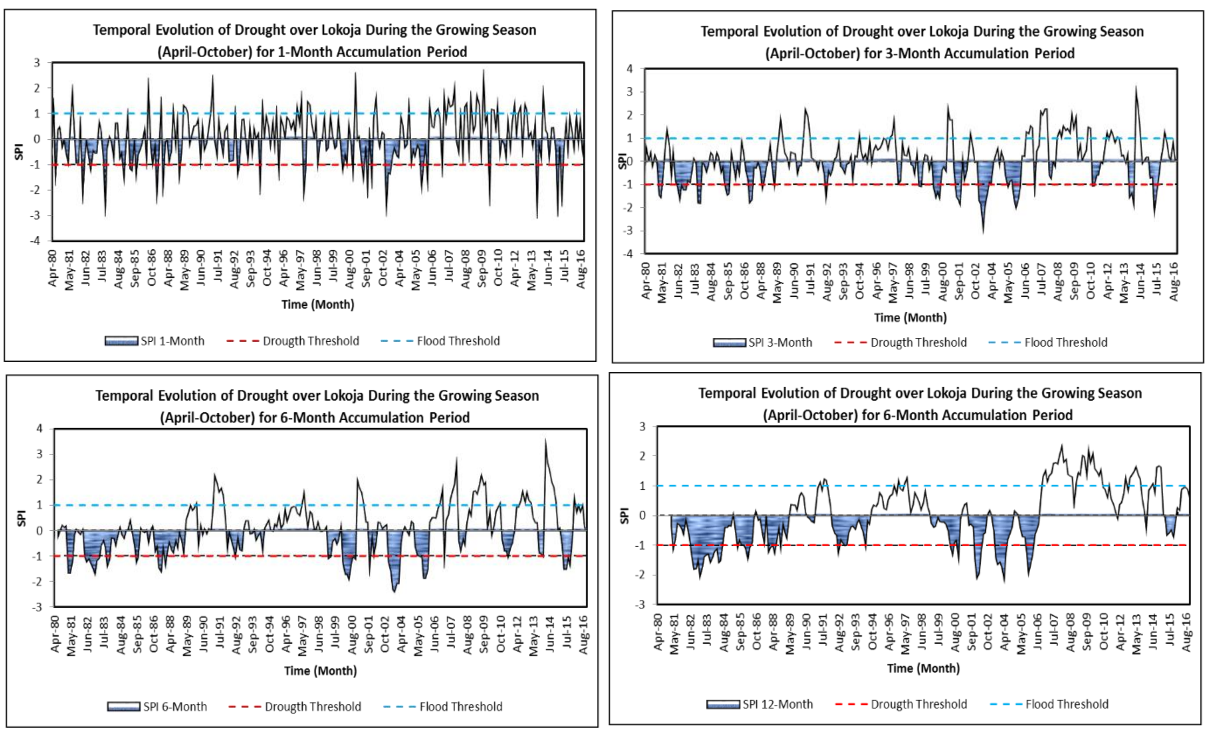

Fig. 9: Lower Niger Watershed 1-, 3-, 6-, and 12- Months SPI time series

To further substantiate the findings of this temporal characterization of drought in the basin, drought rose analysis has been carried out as shown in Fig. 10. Each concentric circle in the drought rose represents different months of the year signifying the duration of each drought year, originating from the zero at the center to increasing durations at the outer circle. The drought years are represented by the spoke or radius of the circle. Results revealed, the number of drought years and durations is unevenly distributed throughout the Niger River basin and most of the long-term drought (i.e., hydrological droughts represented by SPI 12-months) can prevail over a longer period than the short-term droughts represented by SPI 1 to 3-months. The result agrees with the earlier findings of Okpara et al., (2017). In the Upper Niger sub-basin, 50% of the period under study were in a drought of varying duration, with the long-term hydrological drought of 1983-84 with 3 - 7 months duration each year being the most significant. The Inland Delta sub-basin was in a drought of varying durations 35% of the time, with long-term hydrological drought being also the most dominant, especially during the periods 1982 - 83, 1986 - 88, and 1990 - 1992. Drought in this sub-basin, especially, the hydrological droughts could last throughout a cropping season and beyond (i.e., up to 5 - 7 months); hence making drought very critical in the sub-basin, because dry season farming could be severely affected. In the Middle Niger sub-basin, more than 50% of the periods were under drought conditions; with the hydrological drought being dominant especially during 1984 - 85, 1987 - 88, 1993 - 94, and 1997- 98 duration ranging from 2 - 7 months each year. The drought of 1985 as captured in the drought rose analysis was the most significant as it corroborates well with the drying up of the Niger River at Niamey being the first in recorded history. On the other hand, the Lower Niger watershed was 30% of the period under drought, with hydrological drought being dominant in 1982 - 1988 and 2000 - 2005, and their duration in the range of 3 - 7 months. By implication the practice of rain-fed agriculture faces major challenges in the Upper Niger, Inland Delta, and Middle Niger watersheds, farmers in these portions of the basin suffer many significant agricultural losses whenever drought occurs, because of the shorter length of the rainy season; a situation often worsened by longer durations of hydrological drought that affects irrigation farming in those watersheds (Okpara et al., 2017).

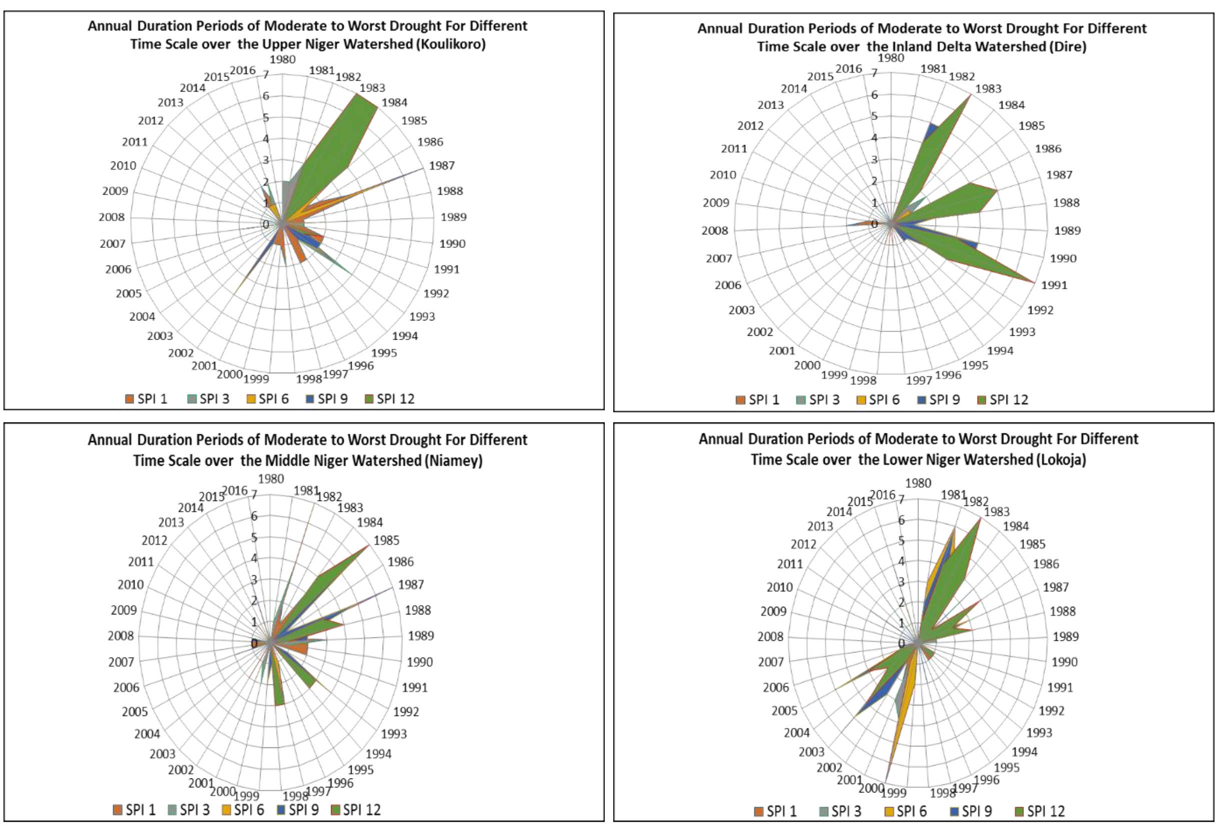

Fig. 10: Drought Rose showing typical the distributions of number drought months and duration in the Niger basin

As evidenced from the obtained results, the most frequently occurring drought events of moderate to extreme intensities and of significant impacts in the Niger basin is hydrological drought, followed by agricultural and meteorological drought events. This agrees with the findings of similar studies in Japan and South Korea by Lee et al. (2012) and Kim et al. (2011) respectively. Therefore, identifying the various drought years within the human society is a critical source of information necessary to establish any drought mitigation and adaptation countermeasure to drought.

In terms of drought recovery in the Niger basin, even with the reanalysis data, the periods are unevenly distributed, which agrees with earlier results of in-situ observation by Okpara et al. (2017). For example, in the Upper Niger sub-basin, the recovery from hydrological drought ~~was~~ fully set in 2004, though before this period, the sub-basin experienced short-term periods of no drought in 1989 and 2002. Whereas recovery from agricultural drought occurred after 2008. Although, the region witnessed some short-term relief from drought in 1993-97 and 1999-2002. The Inland Delta and Middle Niger sub-basins had ~~experienced a~~ respite from the menace of hydrological drought since 1992 and 1989 respectively. The two sub-basins had short-term breaks from agricultural droughts in 1994-2000, 2002-2008, 2010-2014, and 1990-1997, 1999-2015 respectively. Additionally, ~~The further~~ result revealed that the Lower Niger sub-basin came completely out of hydrological drought from 2008, though before then, had some short-term respite in 1989-1999. However, in terms of agricultural drought, the region had a break period only during 1989-1992, 1994 - 2001, and 2007-2014. Though compared to other sub-basins in the Niger Basin, the impacts of drought in the Lower Niger sub-basin have been quite less, because of high impact rainfall in the area.

Results of the spatial characteristics of the drought events of the 1980s showed that almost all parts of the Niger basin witnessed severe to worst meteorological drought conditions depending on the location, which later triggered the occurrence of severe to worst hydrological droughts. Thus, underscoring why the drought disasters of the 1980s were critical in the region.

For example, the Sahelian countries such as Mali, Burkina Faso, Niger Republic, Chad, and parts of Benin, Cameroun, and Nigeria were significantly affected. According to Nicholson, (1989) and Olomoda (2006) cited by Okpara et al., (2017) precipitation deficits during the periods of 1980 reached 60 % of the long-term average and for the first time in recorded history River Niger in Niamey failed to flow (i.e., had a zero flow in 1985). As further shown in Fig. 11, this unusual behavior may have been occasioned by the combined effect of the concurrent occurrence of both short-term agricultural drought (i.e., 3-month SPI map) and long-term hydrological drought (i.e., 12- months SPI) of severe to extreme intensities at Niamey. The severity of the drought as evidenced in the figure and associated disaster extended down even to some coastal areas of the Niger Basin.

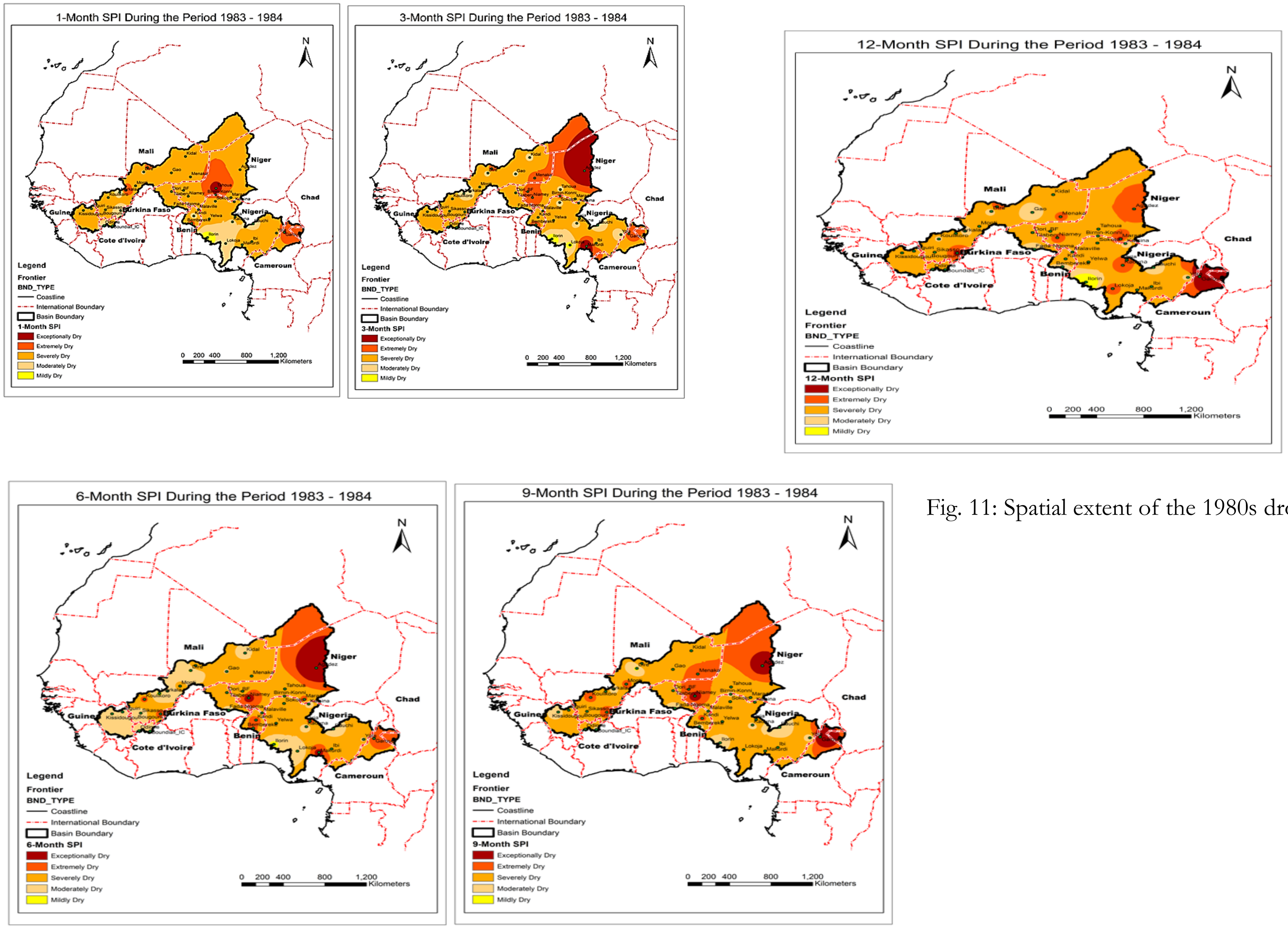

Fig. 11: Spatial extent of the 1980s drought and its intensity

4.0 Linking Science to Practice: Applying r-SPI as a Decision Support Tool in Weather Insurance Contract

In this study also, the authors tried to link the science of SPI metric to the practice of weather index-based insurance by examining how well the reanalysis SPI (r-SPI) reflects the behavior of cereal crop yields across the Niger basin; with the view to be used as a decision support tool in a weather insurance contract. The result from the time series analysis shown in Fig.12 depicts a good match between the cereal yield losses and the occurrence of a drought of moderate to severe intensities across the basin.

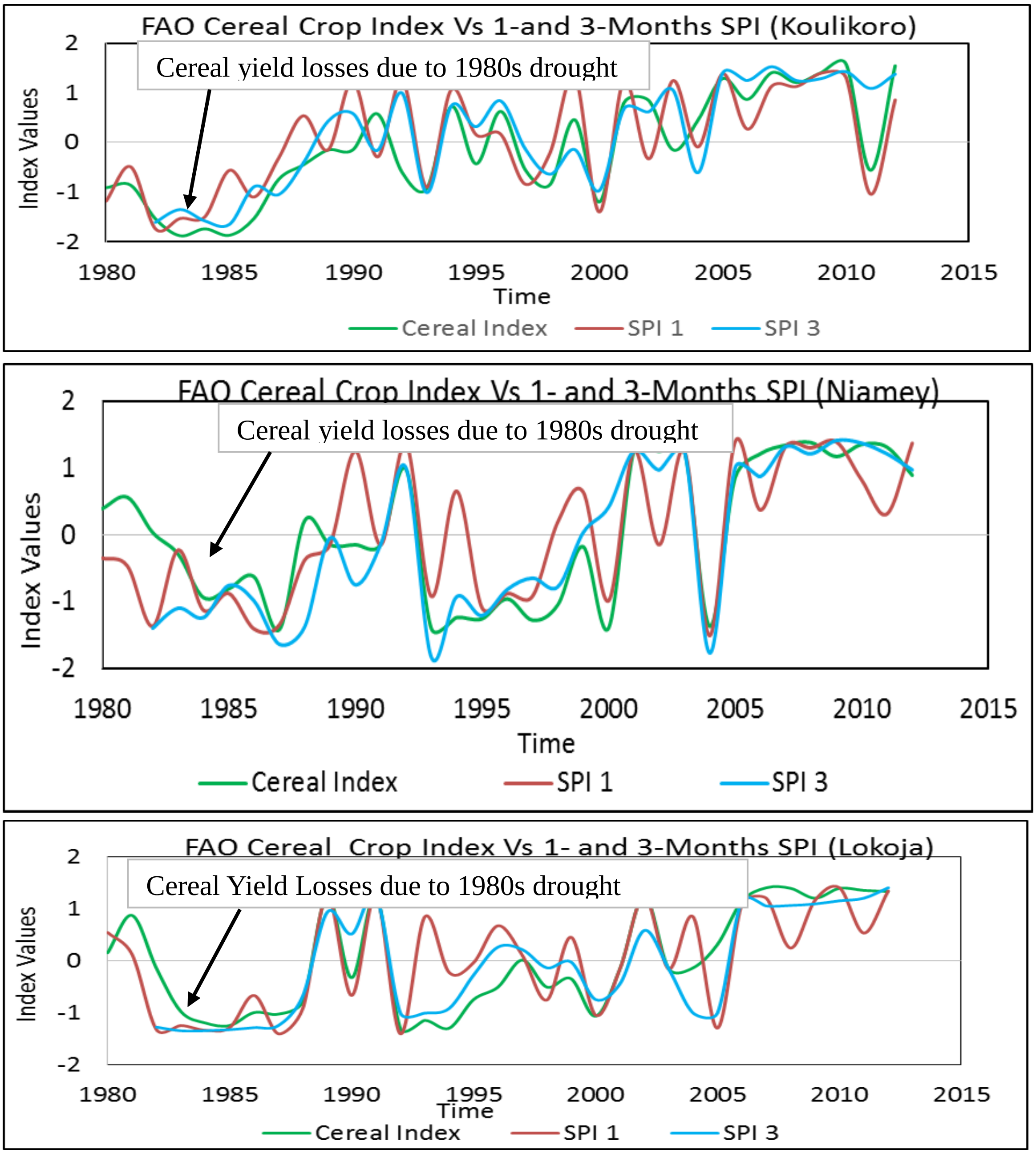

Fig. 12: Time series of 1- and 3-Month RSPI and Standardized Cereal Crop Index

This implies that the index of crop yield variability agrees with the climatic fluctuations in the region, assuming all other influencing factors such as edaphic, pesticide, and fertilizer applications are constant. The close match in the patterns of the indices is a proof that climatic variability remains the bane of rain-fed agricultural production in the basin. Furthermore, SPI values correlated strongly with the standardized cereal crop yield (Fig. 13). For instance, the SPI 3-month correlated very well with cereal yields over the Upper Niger (Koulikoro), Middle Niger (Niamey), and Lower Niger (Lokoja) sub-basins with a correlation coefficient (r) = 0.72, 0.69, and 0.78, thus, explained 85%,83% and 88% of the variances in the crop yields across the basin respectively, which is the most important requirement in the design of weather index insurance program. Thereby making, the SPI 3-month a better proxy for monitoring agricultural drought (WMO, 2012).

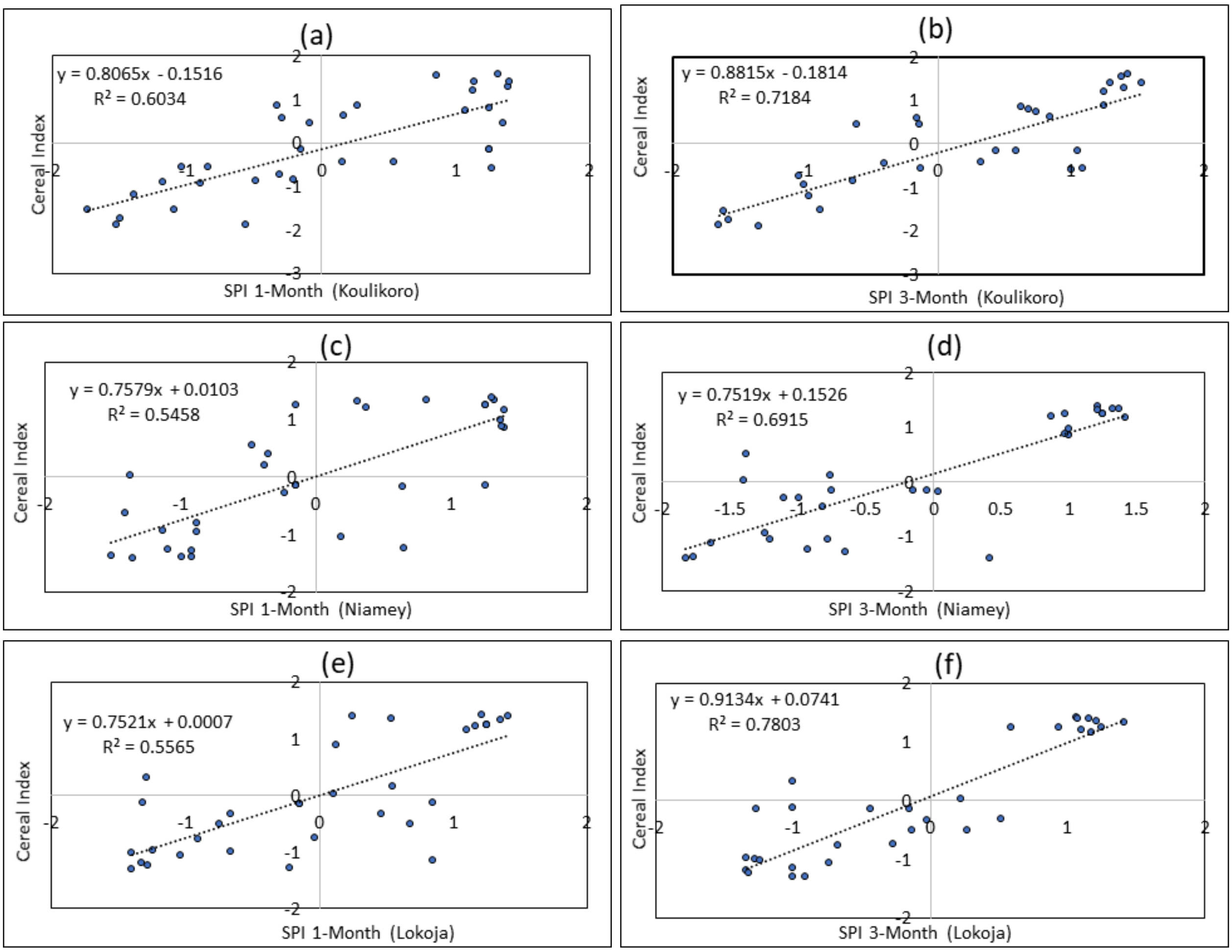

Fig. 13: Scattergram of SPI 1-month versus Cereal Crop Index, and SPI 3-month versus Cereal Crop Index in the Upper Niger, Middle Niger, and Lower Niger sub-basins.

The highest yield loss within the period under consideration was in the 1980s when the drought severity was more. Thereafter, some management practices employed after the 1980s drought episodes may have attributed to the lesser impact on the crop yields. However, compared to the SPI 3-month, the SPI 1-month can explain about 77%, 74%, and 75% of the variance in cereal yield with correlation coefficient(r) = 0.60, 0.55, and 0.56 respectively, whereas the 6-month SPI showed the worst relationship with the yield. This is because a 6-month SPI exhibits a characteristic typical of a long-term drought, while soil moisture or agricultural drought is a short-term drought. Based on the findings, therefore, SPI 3-month is well-suited as a tool for decision making in SPI-based Weather Insurance Contract (SWIC) designed in this study. Also, the obtained result agrees with the earlier findings of Okpara et al. (2017) with in-situ observed data.

Furthermore, the analysis of the equiprobability of the cereal crop yield shown in Fig. 14, revealed the same amount of annual precipitation producing varying cereal crop yields and probability of occurrence across the Niger Basin. For example, 800mm of annual precipitation resulted in yield losses over Upper Niger and Lower Niger sub-basins represented by Standardized Cereal Crop Index (SCCI) values of -0.45 and less than -2.0, and cumulative probability of 0.38 and less than 0.1 respectively.

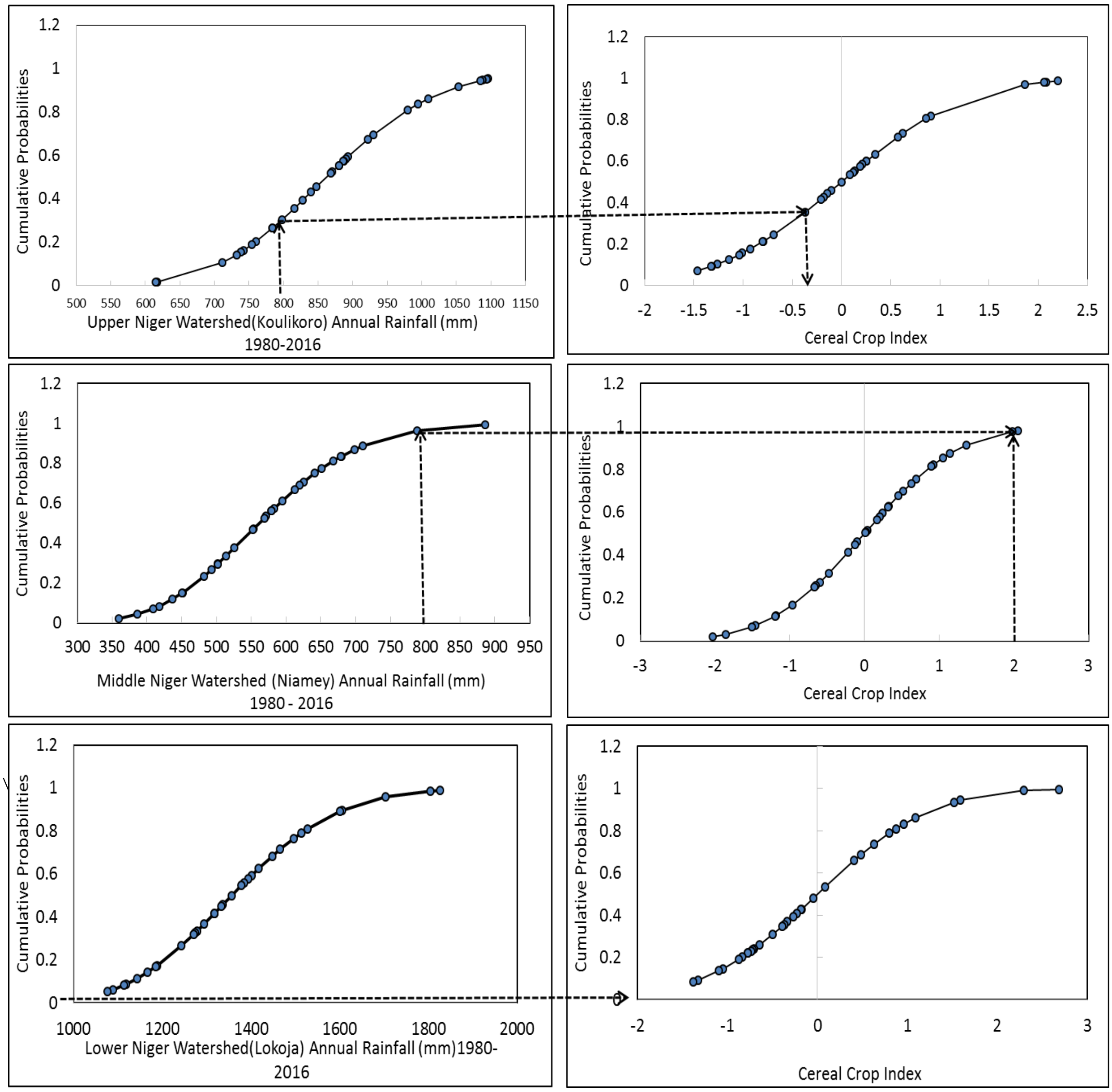

Fig. 14: Equiprobability Transformation of Cereal Yield in the Niger basin

In the Middle Niger sub-basin however, the same amount of precipitation resulted in yield gain with an SCCI value of 2.0 and cumulative probability of 0.98. The findings of this study have, therefore, revealed that the occurrence of weather risk can be circumvented using weather derivatives as a financial instrument in this region. The use of weather derivatives in weather insurance contracts has gained high recognition in the recent times, and spreading very rapidly across the globe, due to its' unique advantage of diversifying and transferring risk (Yang, 2010). In comparison with other prominent weather derivative products such as the Heating Degree Day (HDD) and Cooling Degree Day (CDD) originally introduced by US firm, Enroy Energy Corporation in 1997 (http://www.financialencyclopedia.net/ derivatives/d/degree-day-swap.html), the weather index such as demonstrated in this study is the most active and acceptable one.

This is because the weather index-based insurance products have the latency to offer new solutions that can reduce several of the devastating weather-related impacts on society (Skees and Barnett, 1999; Skees, 1999). The authors, therefore, argued that a conceptual framework of SWIC such as designed and implemented in this study suits the Niger basin well. Relative to every other suitable index, the random variable (precipitation) considered as input in constructing the framework meets the following required criteria proposed by Yang (2010),

(i) it is observable and easily measured; (ii) objective; (iii) transparent; (iv) independently verifiable; (v) reportable promptly; and (vi) stable and sustainable over time.

5.0 Conclusion

It is expedient to analyze drought temporal and geographical extent for a better understanding of the characteristics of the drought phenomenon of any region and adequate planning of its management. The spatiotemporal characterization of historic drought provides vital information on the deficits in water demand resulting from a deficiency in precipitation, and its implications for water resources and the environment, which are essential for drought risk reduction (DRR). Such analysis avails information on drought onset, duration, intensity, frequency, and cessation period, which are useful in drought monitoring and early warning system (EWS), as well as in weather index-based drought insurance. Following the paucity of networks of stations and in-situ observed data, authors leveraged on the availability of reanalysis precipitation data in the characterization of drought events using the World Meteorological Organization (WMO) newly recommended drought index, the Standardized Precipitation Index (SPI) as a measure of drought hazard in the Niger basin.

In the Upper Niger, Inner Delta, Middle Niger, and Lower Niger sub-basins 8, 7, 7, and 6 short-term drought events and 5, 3, 4, and 3 long-term drought events of moderate to extreme intensities were observed respectively between 1980 and 2016. The long-term hydrological drought of 2 - 7 months duration appeared to be the most significant and dominant drought event in the various watersheds of the Niger basin. The study further revealed that in every 10 years, a drought of different durations and intensities occurred in different parts of the Niger basin. Additionally, it is observed that SPI 3-months recommended by WMO as a proxy for monitoring of agricultural drought can explain 83% - 88% of variances in the standardized cereal crop yield in the Niger Basin. Therefore, we argued that farmers engaging in the SPI-based Weather Insurance Contract (SWIC) could be the pathway forward to reducing the negative impacts of the vagaries of severe weather and extreme climate events on the insured farmers in the region, in terms of indemnity payouts, in the event of the occurrence of drought disaster.

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