CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

FACULTY OF ENVIRONMENTAL SCIENCES

MASTER THESIS

THE ESTIMATION OF SPI AND SPEI DROUGHT INDICES

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DIPLOMA THESIS ASSIGNMENT

Valantine Tashia Atoh, BSc

Land and Water Management

Thesis title

The estimation of drougth indices SPI and SPEI

Objectives of thesis

The aim of the thesis is the evaluation of the estimation SPI and SPEI drought indices using different probability distribution functions and fitting methods.

Methodology

The thesis should consist of:

1. The selection of at-least 6 basins from MOPEX dataset

2. The estimation of SPI and SPEI drought indices

3. The evaluation of the impact of the selection of different probability distribution on SPI and SPEI index estimation

4. The evaluation of the impact of the selection of fitting method on SPI and SPEI index estimation

5. The comparison of SPI and SPEI drought indices at selected basins

The proposed extent of the thesis

standard

Keywords

drought, drought index, SPI, SPEI

Recommended information sources

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Beguería, S. – Vicente-Serrano, S. M. SPEI: Calculation of the Standardised Precipitation-Evapotranspiration Index, 2013. R package verze > 1.6.

Mishra, A. K. – Singh, V. P. Drought modeling – A review. Journal of Hydrology. JUN 6 2011, 403, 1-2, s. 157–175.

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DECLARATION

I hereby declare that I am the sole author of the thesis entitled: "The estimation of SPI and SPEI drought indices" under the guidance of Ing.Petr Maca, Ph.D. I duly marked out all quotations. The used literature and sources are stated in the attached list of references.

In Prague on 18.04.2017

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ABSTRACT

The presented paper, model SPEI and SPI drought indices using data from eight US basin.The estimated drought indices are the standardized precipitation index (SPI) and the standardized precipitation evaporation index (SPEI) and were derived for the period of 1948–2003.The meteorological and hydrological data were obtained from MOPEX experiment. This was used for the estimation of the drought indices. The research tries to estimate the SPI and SPEI drought indices within the eight us basins from 1948-2003 and also further tries to evaluate the impact of probability distribution and fitting methods on the estimation process. The research reveals that probability distribution and fitting methods have little or no significant effects on the estimation process of the drought indices estimated. Furthermore, the correlation between basins was calculated and the correlation coefficient between basins reveals that the correlation between the basins is weak or non-existent.

Keywords: Drought, Drought indices; standardized precipitation index; precipitation; The Standardized Precipitation Evapotranspiration Index (SPEI).

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Chapter 1

Introduction

Droughts are natural disasters and extreme climate events which have a large impact in different areas of the economy such as water resources, agriculture, ecosystems, and tourism. Droughts are being recognized as an environmental disaster and have attracted the attention of environmentalists, ecologists, hydrologists, meteorologists, geologists and agricultural scientists. They also, occur in climatic zones, such as high as well as low rainfall areas and are mostly related to the reduction in the amount of precipitation received over an extended period of time, such as season or a year. The following plays a significant role in the occurrence of droughts in our present day, temperatures, high winds, low relative humidity, timing and characteristics of rain, including distribution of rainy days during crop growing seasons etc. In contrast to aridity, which is a permanent feature of Climate and is restricted to low rainfall areas (Wilhite, 1992),

Furthermore, the demand for water has increased greatly and even water scarcity has been occurring almost every year in many parts of the world due to the growth of population, the expansion of agricultural sectors, energy sectors and industrial sectors. Other factors, such as climate change and contamination of water supplies, have further contributed to the water scarcity. In recent years, floods and droughts have been experiencing higher peaks and severity levels. The period between extreme events seems to have become shorter in certain regions. Lettenmaier et al. (1996) and Aswathanarayana (2001) have made references to this change in the occurrence of extreme hydrologic events.

Also, drought's impact on both surface and groundwater resources can lead to reduced water supply, deteriorated water quality, crop failure, reduced range productivity, diminished power generation, disturbed riparian habitats, and suspended recreation activities, as well as affect a host of economic and social activities (Riebsame et al., 1991). In addition droughts also affect water quality, as moderate climate fluctuations alter hydrologic regimes that have substantial effects on the lake chemistry (Webster et al., 1996). Sediment, organic matter, and nutrients are transported to surface waters by runoff, a pathway that is interrupted during droughts.

Aim: Estimation of SPI and SPEI indices and describe the impact of probability distribution and fitting methods on the estimation process.

Objectives

There are basically three objectives in this research which is as listed below.

1) The evaluation of the impact of the selection of different probability distribution on SPI and SPEI index estimation.

2) The evaluation of the impact of the selection of fitting method on SPI and SPEI index estimation.

3) The comparison of SPI and SPEI drought indices at selected basins

Chapter 2

LITERATURE REVIEW

Need for Drought Research

The assessment of droughts is of vital importance for freshwater management and planning processes. The understanding of the historical droughts in a particular region will as well influence the impacts of droughts during their occurrences. Therefore, understanding different concepts of droughts will be helpful for developing models to investigate different drought properties.(Mishra and Singh., 2010).

In addition to the above, the first step that we can take to mitigate drought is to understand drought and our environment. It is very important that we all understand drought and also very important that we understand the environment where we live. Just like you have certain characteristics, the environment where you live also has characteristics. The climate where you live can be thought of as a characteristic of your environment. Other characteristics of your environment might be whether there are forests or grasslands, or whether you live in the mountains or by a river or ocean. The characteristics of your environment hold clues about how often you might expect to experience drought, what the impacts of drought would be, and steps you and your community can take to protect yourselves and your environment from drought. (National drought mitigation center, http://drought.unl.edu).

Furthermore, droughts are ecologically and economically destructive, which affects millions of people in the world each year. Severe drought conditions can impact agriculture, water resources, tourism, ecosystems, and basic human welfare. The effect of drought varies with coping capabilities. For example, people living in regions with advanced irrigation systems, such as those in developed countries, can mitigate the impacts of drought much better than farmers in Africa and other developing countries who often have limited tools to combat droughts and other natural disasters. As global warming continues, the limited capabilities in developing countries will become an increasingly important issue in global efforts to mitigate the negative impact of climate change.(Dai,2011)

Impact of climate change on droughts

In the twenty-first century, climate change is known as one of the major threats for the planet earth. According to the Intergovernmental Panel on Climate Change (IPCC) report (IPCC, 2007), instrumental observations over the past 157 years show that temperatures at the surface have increased globally, with significant regional variations. For the global average, warming in the last (20th) century has occurred in two phases, from the 1910s to the 1940s (0.35 _C), and more strongly from the 1970s to the present (0.55 _C). An increasing rate of warming has taken place over the last 25 years, and 11 of the 12 warmest years on record have occurred in the past 12 years. Generally, this warming intensifies the global hydrological cycle (e.g., Milly et al., 2002) and Clark et al., (1999), further established that the earth's mean surface temperature has been increasing following the last glacial maximum 21,000 years ago, thus increasing the globally averaged precipitation, evaporation, and runoff. The consequence of global warming is not the change in the averages but the overall increase of extreme events. Amongst these extreme meteorological events, droughts are possibly the most slowly developing ones, that often have the longest duration, and at the moment the least predictability among all atmospheric hazards. We can also trace that several Studies have been carried out on how climate change will affect various ecosystems, these studies were been conducted as an international effort on many fronts. Most of these studies address the effect in terms of changes in discharge caused by changed precipitation and temperature, the effects varying widely with the adopted scenarios and catchment type (e.g., Gleick, 1987; Karl and Riebsame, 1989; Lettenmaier and Gan, 1990; Panagoulia, 1992). However, analyses of changes in drought characteristics due to climate change impacts have not been explored fully. Recent studies on understanding drought impacts, Szep et al. (2005) found out that local soil moisture conditions in East Hungary became drier in the 20th century, parallel to the hemispherical changes. Andreadis and Lettenmaier (2006) also examined agricultural and hydrological droughts in USA, and observed that for the most part, droughts have, become shorter, less frequent, and cover a smaller portion of the country over the last century except southwest and parts of the interior of the west, where trends in drought characteristics, that are mostly opposite to those for the rest of the country, especially in the case of drought duration and severity, have increased. In another study, Mishra and Singh (2009) highlighted the changes in drought severity-area-frequency due to climate change scenarios and compared with historical droughts for Kansabati River basin in India. It is now accepted that droughts in future pose a threat to climate-sensitive economic sectors, specifically agriculture, and have therefore necessitated the assessment of potential impacts of climate change on crop production at various scales. This will help develop measures to reduce agricultural vulnerability and thereby secure livelihoods of those who depend on agriculture. The following section discusses how droughts have affected different continents around the globe during recent decades to draw attention to the necessity for understanding droughts.

History about drought

Drought is a normal part of climate variations. Tree-ring and other proxy data, together with instrumental records, have revealed that large-scale droughts have occurred many times during the past 1000 years over many parts of the world, including North America, Mexico, Asia, Africa and Australia. (Mishra and Singh, 2011)

Long-term Historical Perspective of drought in West Africa

West Africa, where the severe and widespread Sahel droughts of the 1970s and 1980s devastated the local population, has been the subject of a very large number of studies. Proxy data for African lake levels reveal that very dry and wet periods occurred in the early and late part of the 19th century, respectively, over West and East Africa. The recent Sahel drought is not unusual in the context of the past three millennia, which indicates that natural monsoon variations in West Africa are capable of causing severe droughts in the future. Many studies have shown that the recent Sahel droughts resulted primarily from a southward shift of the warmest SSTs and the associated inter-tropical convergence zone (ITCZ) in the tropical Atlantic and the steady warming in the Indian Ocean, which enhances subsidence over West Africa. We have seen that reduced vegetation cover and increase surface evaporation as a result of increase population and large-scale deforestation which expose the soils to direct sun rays may have provided a positive feedback that enhances and prolongs the droughts.

Impact of droughts around the globe during recent decades

Droughts produce a complex web of impacts that affects many sectors of the society, including the economy. They are a widespread phenomenon (Kogan, 1997) since about half of the earth's terrestrial surfaces are susceptible to them. More importantly, almost all of the major agricultural lands are located there (USDA, 1994). Of all the recants natural hazards, droughts have had the greatest detrimental impact in the world.(Bruce, 1994; Obasi, 1994). In recent years, large-scale intensive droughts have been observed on all continents, affecting large areas in Europe, Africa, Asia, Australia, South America, Central America, and North America (Le Comte, 1995; Le Comte, 1994) and because of this there is an increase in economic and social costs which have led to increasing attention to droughts (Downing and Bakker, 2000).

The impact of droughts on African continents will be discussed below. Since the late 1960s, the Sahel semiarid region in West Africa between the Sahara desert and the Guinea coast rainforest has experienced a drought of unprecedented severity in recorded history. The drought has had a devastating impact on this ecologically vulnerable region and was a major reason for the establishment of the United Nations Convention on Combating Desertification and Drought (Zeng, 2003). While the frequency of droughts in this region is thought to have increased from the end of the 19th century, as the region witnesses three long droughts events which have dramatic environmental and societal effects upon the Sahel nations. Famine followed severe droughts in the 1910s, the 1940s, and the 1960s, 1970s, and 1980s; although a partial recovery occurred from 1975–1980.While at least one particularly severe drought has been confirmed in each century since the 1600s, the frequency and severity of the recent Sahelian drought stand out. Famine and dislocation on a massive scale from 1968 to 1974 and again in the early and mid 1980s-was blamed on two spikes in the severity of the 1960– 1980s drought period (Batterbury and Warren, 2001)

Classification of Droughts

The droughts are generally classified into four categories (Wilhite and Glantz, 1985; American Meteorological Society, 2004), which include:

A) **Meteorological Drought**: Meteorological drought is defined as a lack of precipitation over a region for a period of time. Precipitation has been commonly used for meteorological drought analysis (Pinkeye,1966; Santos, 1983; Chang, 1991; Eltahir, 1992). Considering drought as precipitation deficit with respect to average values (Gibbs, 1975), several studies have analyzed droughts using Monthly precipitation data. Other approaches analyze drought duration and intensity in relation to cumulative precipitation shortages (Chang and Kleopa, 1991; Estrela et al., 2000).Meteorological drought is also considered or defined as a period of months to years with below-normal precipitation. It is often accompanied by above-normal temperatures and precedes and causes other types of droughts. Meteorological drought is caused by persistent anomalies (e.g., high pressure) in large-scale atmospheric circular patterns, which are often triggered by anomalous tropical sea surface temperatures (SSTs) or other remote conditions. (Dai, 2011)

B) **Hydrological Drought:** Hydrological drought is related to a period with inadequate surface and subsurface water resources for established water users of a given water resources management system. It occurs when river stream flow and water storages in aquifers, lakes, or reservoirs fall below long-term mean levels.(Dai,2011) Stream flow data have been widely applied for hydrologic drought analysis (Dracup et al., 1980; Sen, 1980; Zelenhasic and Salvai, 1987; Chang and Stenson, 1990; Frick et al., 1990; Mohan and Rangacharya, 1991; Clausen and Pearson, 1995). From regression analyses relating droughts in stream flow to catchment properties, it is found that geology is one of the main factors influencing hydrological droughts (Zecharias and Brutsaert, 1988; Vogel and Kroll, 1992).

C) **Agricultural Drought:** Agricultural drought, usually, refers to a period with declining soil moisture and consequent crop failure without any reference to surface water resources. A decline of soil moisture depends on several factors which affect meteorological and hydrological droughts along with differences between actual evapotranspiration and potential evapotranspiration. Agricultural drought is referred as a period with dry soils that results from below-average precipitation, intense but less frequent rain events, or above-normal evaporation, all of which lead to reduced crop production and plant growth.

Also, Plant water demand depends on prevailing weather conditions, biological characteristics of the specific plant and stage of growth, and the physical and biological properties of soil. Several drought indices, based on a combination of precipitation, temperature and soil moisture, have been derived from studying agricultural droughts.

D) **Socio-Economic Drought:** Socioeconomic drought is associated with failure of water resources systems to meet water demands and thus associating droughts with the supply of and demand for an economic good (water) (AMS, 2004). Socioeconomic drought occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply. Several studies have discussed these four types of droughts; however, it will be useful and important to introduce groundwater drought as a type of drought which has not been included in the classification of droughts. To date, little research has been done on the occurrence and propagation of droughts in groundwater. The following section discusses groundwater drought in more detail as this can be treated as a new type of drought

Droughts as Natural Hazards

A natural hazard is a threat of a naturally occurring event that will have a negative effect on people or the environment and drought is a kind of natural hazard which is further aggravated by growing water demand. Some of the reasons for the occurrence of droughts are complex because they are not dependent sorely on the atmosphere but also on the hydrologic processes which feed moisture to the atmosphere. Immediately dry hydrologic conditions are established the positive feedback mechanism of droughts sets in, where the moisture depletion from upper soil layers decreases evapotranspiration rates, which, in turn, lessen the atmospheric relative humidity. Also, the lesser the relative humidity the less probable the rainfall becomes, as it will be harder to reach saturation conditions for a regular low-pressure system over the region. In addition, only disturbances which carry enough moisture from outside the dry region will be able to produce sufficient rainfall to end drought conditions (Bravar and Kavvas, 1991).

However, droughts is being rank first among all natural hazards when measured in terms of the number of people affected (Obasi, 1994; Hewitt,1997; Wilhite,2000b). Though it’s a natural hazard, droughts differ from other natural hazards in several ways (Wilhite, 2000a). First, the onset and the end of a drought are difficult to determine, the impacts of a drought increase slowly, often accumulate over a considerable period and may linger for years after termination. Therefore, a drought is often referred to as a creeping phenomenon. Second, it is difficult to define a drought which leads to confusion for not having a universal definition of drought. Third, drought impacts are non-structural and spread over large geographical areas than damages that may result from other natural hazards. In contrast to floods, hurricanes, earthquakes, and tornadoes a drought affects water bodies of water resources structures and it seldom results in structural damage. For this reason, the quantification of the impact and the provision for relief are far more difficult for droughts than for other natural hazards (Wilhite, 2000a). Fourth, human activities can directly trigger a drought, unlike other natural hazards, with exacerbating factors such as over farming, excessive irrigation, deforestation, over-exploiting available water, and erosion, adversely impacting the ability of the land to capture and hold water. Bryant (1991) ranked hazard events based on their characteristics and impacts. Key hazard characteristics used for ranking included the degree of severity, the length of the event, total areal extent, total loss of life, total economic loss, social effect, long-term impact, suddenness, and occurrence of associated hazards. It was found that drought stood first based on most of the hazard characteristics. Other natural hazards, which followed droughts in terms of their rank, are tropical cyclones, regional floods, earthquakes, and volcanoes.

Drought Indices

The drought indices are essential tools for explaining the severity of drought events. They are mainly represented in a form of time series and are used in drought modeling and forecasting (Ashok and Vijay, 2011).The inter-comparison of different drought indices connected with the development of forecasting tools has been studied in a large number of research studies. (Ntale and Gan, 2003).Drought Indices and their Application to East Africa .This article analyses the properties of three popular drought indices and modifies them where necessary to increase their general effectiveness and dependability in detecting droughts. Also, it further identifies some assessment criteria for determining the most appropriate drought index for detecting the initiation, evolution, and termination of droughts on a regional basis. The indices chosen for this study were as follows, the standardized precipitation index (SPI), the Palmer drought severity index (PDSI) and the Bhalme–Mooley index (BMI) partly because they are non-basin-specific indices that can theoretically be used for drought comparisons in regions of different climates.In addition to the above, (Haslinger et al,2014), Exploring the link between meteorological drought and streamflow. Four drought indices considering different components of the catchment water balance are tested. This article assesses the quality of the link using rank correlation analysis and the probability of detecting low-flow events by hit-scores. Meteorological Drought Indices used in this survey were as follows,

1) The Standardized Precipitation Index (SPI), which was introduced by McKee et al. (1993) and provides a very simple approach for assessing either dry or wet conditions, with the possibility to consider different time scales. The SPI has proven to be a useful measure to describe drought events (Hayes et al., 1999; Labedzki, 2007; Du et al., 2013).

2) The Standardized Precipitation-Evapotranspiration Index (SPEI) which was suggested by Vincente-Serrano et al. (2010). It's a drought index which is based on the concept of the SPI, but with the extension of considering potential evapotranspiration (PET) as well. The Standardized Precipitation-Evapotranspiration Index (SPEI) is similar to the SPI. The SPEI can be used to assess dry or wet periods on different time scales. The SPEI algorithm uses monthly values of precipitation (Pi) and potential evapotranspiration (PETi) to calculate the climatic water balance Di of month i by a simple subtraction equation which is one of the indices use in this research.

Di= Pi- PETi .3) The Self-Calibrating Palmer Drought Severity Index (scPDSI).This index is based on a simple soil moisture balance accounting scheme (SMBAS) and was introduced by Palmer (1965).

4) The Palmer's Z-Index.

Some reviews of significant drought events, their impacts, description, mitigation, and propagation in time are presented in detail in (Dai, 2011), Drought under global warming. This article reviews recent literature on the drought of the last millennium, followed by an update on global aridity changes from 1950 to 2008. Several drought indices have been derived in recent decades. Commonly, a drought index is a prime variable for assessing the effect of a drought and defining different drought parameters, which include intensity, duration, severity and spatial extent. It should be noted that a drought variable should be able to quantify the drought for different time scales for which a long time series is essential. The most commonly used time scale for drought analysis is a year, followed by a month. Although the yearly time scale is long, it can also be used to abstract information on the regional behavior of droughts. The monthly time scale seems to be more appropriate for monitoring the effects of a drought in situations related to agriculture, water supply and groundwater abstractions (Panu and Sharma, 2002). A time series of drought indices provides a framework for evaluating drought parameters of interest. A number of different indices have been developed to quantify a drought, each with its own strengths and weaknesses. They include the Palmer drought severity index (PDSI; Palmer 1965), rainfall anomaly index (RAI; van Rooy, 1965), deciles (Gibbs and Maher, 1967), crop moisture index (CMI; Palmer, 1968), Bhalme and Mooly drought index (BMDI; Bhalme and Mooley, 1980), surface water supply index (SWSI; Shafer and Dezman, 1982), national rainfall index (NRI; Gommes and Petrassi, 1994), standardized precipitation index (SPI; McKee et al., 1993, 1995), and reclamation drought index (RDI; Weghorst, 1996). The soil moisture drought index (SMDI; Hollinger et al., 1993) and crop-specific drought index (CSDI; Meyer and Hubbard, 1995) appeared after CMI. Furthermore, CSDI is divided into a corn drought index (CDI; Meyer and Pulliam, 1992) and soybean drought index (SDI; Meyer and Hubbard, 1995), and vegetation condition index (VCI; Liu and Kogan, 1996). Heim (2002) gave a comprehensive review of 20th-century drought indices used in the United States. Based on the studies for drought indices, practically all drought indices use precipitation either singly or in combination with other meteorological elements, depending upon the type of requirements, which were also suggested by WMO (1975). For example, a combination of hydro-meteorological variables includes temperature and precipitation (Marcovitch’s index, 1930; Palmers index, 1965; Crop moisture index, 1968), precipitation and soil moisture (Moisture adequacy index,1957; Keetch-Bryam drought index, 1968) and only precipitation (SPI, 1993).

The droughts studied in this research were described using two drought indices, which are:

1) **The standardized precipitation index, (SPI index)**.The Standardized Precipitation Index was developed to improve drought detection and monitoring capabilities. The SPI has several characteristics that are an improvement over previous indices, including its simplicity and temporal flexibility that allow its application for water resources on all timescales. (Hayes et al, 1996).Furthermore, Cancelliere et al. (2007) use the Standardized Precipitation Index (SPI) for describing and comparing droughts among different time periods and regions with different climatic conditions.

2) **The standardized precipitation evapotranspiration index (SPEI index).** In 2010 the standardized precipitation evapotranspiration index (SPEI) was developed and has been used in an increasing number of climatology and hydrology studies. Beguería et al,(2014), describe

computing options that provide flexible and robust use of the SPEI. They went further to present methods for estimating the parameters of the log-logistic distribution for obtaining standardized values, methods for computing reference evapotranspiration (ET0), and weighting kernels used for calculation of the SPEI at different time scales. The SPEI is based on precipitation and temperature data, and it has the advantage of combining multiscalar character with the capacity to include the effects of temperature variability on drought assessment. The procedure to calculate the index is detailed and involves a climatic water balance, the accumulation of deficit/surplus at different time scales, and adjustment to a log-logistic probability distribution.(Aula,2009). The SPEI uses the monthly (or weekly) difference between precipitation and PET. This represents a simple climatic water balance (Thornthwaite 1948) that is calculated at different time scales to obtain the SPEI. Aula,(2009), A Multiscalar Drought Index Sensitive to Global Warming, gives you details and sample methods used for the calculation of PET.

Comparison of drought indices

We can trace from several articles that many different authors have made several attempts to compare different indices so as to find the most suitable indices for different specific objectives of drought monitoring. As a result of these comparisons, there has been a lot of comparison between SPI and PDSI used for monitoring droughts. Some of the differences could be traced in different articles which were written by different authors in different years. Some of the differences are as follows: a) In a case study carried out in the USA by Guttman (1999) reveals that special characteristics of PDI vary from site to site while those of SPI do not vary from site to site. In addition to the above, PDI has a complex structure with an exceptionally long memory, while SPI is easily interpreted, simple moving average process. Therefore, SPI can be used as the primary drought index, because it is simple, spatially invariant in its interpretation, and probabilistic, so it can be used in risk and decision analysis (Guttman, 1998). b) Furthermore, Sims et al., (2002) reveals that SPI is more representative of short-term precipitation than PDSI and thus is a better indicator for soil moisture variation and soil wetness c) Also, Quiring and Papakyriakou, (2003) proves that SPI is a better predictor of crop production, as it represents the moisture state of soil better. (d) SPI provides a better spatial standardization than does PDSI with respect to extreme drought events as stated by (Lloyd-

Hughes and Saunders, 2002). (e) In addition, Keyantash and Dracup (2002) found that SPI was a valuable estimator of drought severity after the evaluation of 14 well knows drought indices using a weighted set of six evaluation criteria. (f) Finally, a case study in Texas, by Hayes et al. (1999) reveals that SPI detects the onset of a drought earlier than PDSI.

Chapter 3

MATERIAL AND METHODS

Material

The Dataset Description

The data used for the estimation of the drought indices was obtained from eight different US basins. The data were part of large dataset prepared within the MOPEX experiment framework. (Duan et al., 2006).The MOPEX dataset provides the benchmark hydrological and meteorological data, which were explored in a large number of environmentally oriented studies.(Ao T., Ishidaira H., Takeuchi K., et al.,2006).

Table1. Showing the basins details

USGS basin ID	Longitude	Latitude	Area(sq. mi.)	Annual precipitation/ annual potential evaporation ratio	Annual runoff/annual precipitation ratio	Annual evaporation/annual potential evaporation ratio
1138000	-71.986	44.154	395	1.52	0.45	0.84
3213000	-81.844	37.486	504	1.54	0.45	0.84
4198000	-83.1589	41.3078	1251	1.05	0.31	0.72
6191500	-110.794	45.1119	2623	1.38	0.40	0.83
8032000	-95.4306	31.8922	1145	0.73	0.19	0.59
12413500	-116.307	47.5639	1220	1.13	0.33	0.76
3010500	-78.3864	41.9633	550	1.60	0.47	0.85
14321000	-123.554	43.5861	3683	2.16	0.56	0.95

The details on the table show that there is no relationship between them ie the 8 different basins have different coordinates (longitude and latitude), area etc.

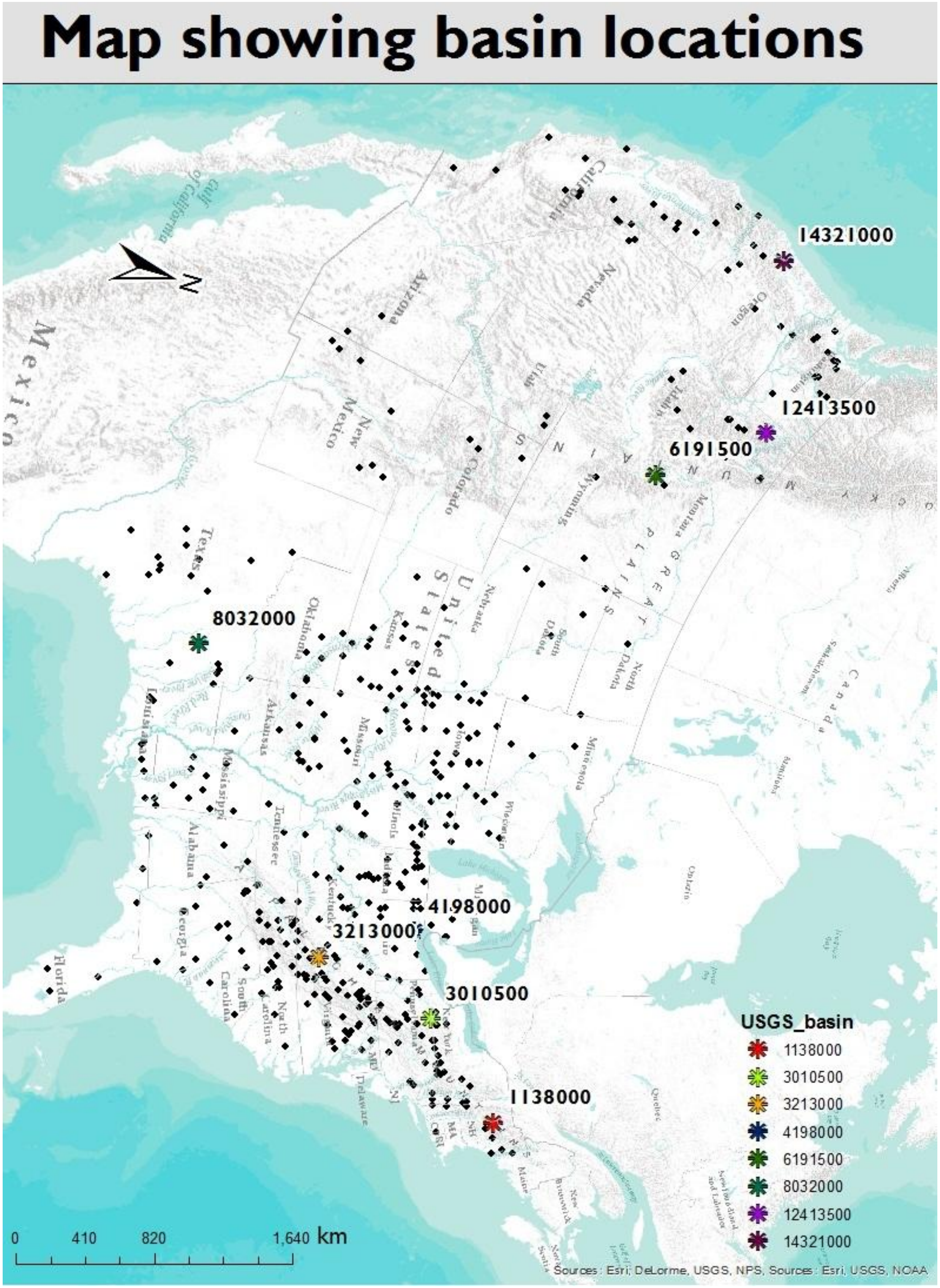


Figure 1.Map showing the basin locations

V5= precipitation (mm)

V5= PET (mm).

Table 2.Statistics of precipitation and PET

Statistics/basins	1138000	3213000	4198000	6191500	8032000	12413500	3010500	14321000
min(v5)	13.76	1.24	7.90	2.26	2.53	0.16	13.09	0.01
1st Qu(v5)	66.90	61.92	49.04	39.51	45.38	52.59	58.42	34.00
median(v5)	87.46	83.82	71.62	55.78	79.60	86.20	81.38	80.32
mean(v5)	93.42	88.80	75.58	58.96	88.99	100.10	85.66	106.40
3rd Qu(v5)	115.30	111.90	99.24	75.02	119.50	137.70	104.60	155.40
max(v5)	260.10	245.30	240.80	202.30	396.50	375.10	282.50	558.80
min(v6)	4.70	7.286	4.987	0.00	43.64	0.00	15.68	0.191
1st Qu(v6)	19.41	21.960	24.790	10.66	62.79	16.95	28.27	21.420
median(v6)	57.65	61.530	70.680	58.19	110.20	63.09	58.96	63.110
mean(v6)	58.05	61.940	71.130	62.07	110.50	64.49	59.24	63.600
3rd Qu(v6)	97.52	102.100	118.500	109.70	159.10	111.20	90.79	106.400
max(v6)	113.70	117.300	140.000	140.30	181.60	137.30	105.10	130.500

The table 2.Shows the statistics of the precipitation and PET of all the 8 basins, we can view that there is no relationship between the data.

Methods

A) Standardized Precipitation Index (Spi). The Standardized Precipitation Index (SPI) was developed by McKee *et al.* (1993) for the purpose of defining and monitoring drought. Among others, the Colorado Climate Center, the Western Regional Climate Center, and the National Drought Mitigation Center use the SPI to monitor the current status of drought in the United States. The nature of the SPI allows an analyst to determine the rarity of a drought or an anomalously wet event at a particular time scale for any location in the world that has a precipitation record. The SPI is based on precipitation alone. Its fundamental strength is that it can be calculated for a variety of timescales. This versatility allows the SPI to monitor short-term water supplies, such as soil moisture, important for agricultural production, and longerterm water resources such as groundwater supplies, stream flow, lakes and reservoir levels. The ability to examine different timescales also allows droughts to be readily identified and monitored for the duration of the drought. (Hayes et al, 1996) .Thom (1966) found the gamma distribution to fit climatological precipitation time series accurately. The gamma distribution is defined by its frequency or probability density.

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\alpha}\tau(\hat{\alpha})}\int_0^x x^{\alpha-1}\, e^{\frac{-x}{\hat{\beta}}}dx \;\; x > 0$$

Where:

$\alpha > 0$ $\qquad$ α *is a shape parameter*

$\beta > 0$ $\qquad$ β *is a sacle parameter*

$x > 0$ $\qquad$ x *is the precpitation amount*

$\tau(\alpha) = \int_0^\infty y^{\alpha-1}\, e^{-y}\, dy$ $\qquad$ $\tau(\alpha)$ *is the gamma function*

Computation of the SPI involves fitting a gamma probability density function to a given frequency distribution of precipitation totals for a station. The alpha and beta parameters of the gamma probability density function are estimated for each station, for each time scale of interest (3 months, 12 months, 48 months, etc.), and for each month of the year. From Thom (1966), the maximum likelihood solutions are used to optimally estimate α and β:

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

$$\hat{\beta} = \frac{\bar{x}}{3}$$

Where:

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

n= number of precipitation observations

The resulting parameters are then used to find the cumulative probability of an observed precipitation event for the given month and time scale for the station in question. The cumulative probability is given by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\alpha}\tau(\hat{\alpha})}\int_0^x x^{\alpha-1}\, e^{\frac{-x}{\hat{\beta}}}dx$$

The SPI index is based on the evaluation of precipitation data. The precipitation data are linked to the selected probability distribution, which is further, standardized using the normal distribution with zero mean and standard deviation of one. SPI index is often expressed as a meteorological drought index as stated in (Belayneh, et al, 2014) and it is used for the assessment of agricultural and hydrological droughts. Hayes, et al,(1996) tries to illustrate some case studies where this index was being used.In the case of the 1996 drought in the southwestern and southern plains in the United States was examined using the SPI. The SPI proves that it is a tool that should be used operationally as part of a state, regional or national drought watch system in the United States. (Hayes, et al, 1996).Furthermore, the estimation of SPI consists of the determination of probability distribution of analyzed precipitation data, the calculation of probabilities for measured precipitation data from cumulative distribution function of a fitted probability distribution, and the application of the inverse of the distribution function of normalized normal distribution on probabilities. (Hayes, et al, 1996) .In addition to the above, the standardized precipitation index (SPI) for any location is calculated, based on the long-term precipitation record for the desired period. This long-term record is fitted to a probability distribution, which is then transformed to a normal distribution so that the mean SPI for the location and desired period is zero (McKee et al., 1993; Edwards and McKee, 1997). The fundamental strength of SPI is that it can be calculated for a variety of time scales. This allows SPI to monitor short-term water supplies, such as soil moisture which is important for agricultural production, and long-term water resources, such as groundwater supplies, stream flow, and lake and reservoir levels. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, streamflow, and reservoir storage reflect the long-term precipitation anomalies. For example, Szalai et al. (2000) examined how strong the connection of SPI is with hydrological features, such as streamflow and groundwater level at stations in Hungary. Correlation of SPI with stream flow was the highest on a 2-month timescale, while for groundwater levels the best correlations were found at widely different time scales. They also concluded that agricultural drought (proxied by soil moisture content) was replicated best by SPI on a scale of 2–3 months. SPI has been used for studying different aspects of droughts, for example, forecasting (Mishra and Desai, 2005a; Mishra et al. 2007), frequency analysis (Mishra et al. 2009), spatiotemporal analysis (Mishra and Desai, 2005b; Mishra and Singh, 2009) and climate impact studies (Mishra and Singh, 2009).

Limitations of SPI; The length of precipitation record and nature of probability distribution play an important role for calculating SPI and the following section below discusses the limitations of SPI.

a) **The length of precipitation record;** the length of a precipitation record has a significant impact on the SPI values. Similar and consistent results are observed when the SPI values, computed from different lengths of record, have similar gamma distributions over different time periods. However, the SPI values are significantly discrepant when the distributions are different. It is recommended that the SPI user should be aware of the numerical differences in the SPI values if different lengths of record are used in interpreting and making decisions based on the SPI values. For example, Wu et al. (2005) investigated the effect of the length of record on the SPI calculation by examining correlation coefficients, the index of agreement, and the consistency of dry/wet event categories between the SPI values derived from different precipitation record lengths. The reason for the discrepancy in the SPI value is due to changes in the shape and scale parameters of the gamma distribution when different lengths of record are involved.

b) **Probability distributions**: The use of different probability distributions affect the SPI values as the SPI is based on the fitting of a distribution to precipitation series. Some of the commonly applied distributions include: gamma distribution (McKee et al., 1993; Edwards and McKee, 1997; Mishra and Singh, 2009); and Pearson Type III distribution (Guttman, 1999); and lognormal, extreme value, and exponential distributions have been widely applied to simulations of precipitation distributions (Lloyd-Hughes and Saunders, 2002; Madsen et al., 1998; Todorovic and Woolhiser, 1976; Wu et al., 2007).Two types of problems arise: (i) When SPIs are calculated for long time scales (longer than 24 months) fitting a distribution might be biased due to the limitation in data length and it is true that when finer resolutions of spatial analysis need to be investigated, long data sets are not available in many catchments around the world.Lloyd-Hughes and Saunders (2002) and Sonmez et al. (2005) reported biased SPI values.

(ii) For dry climates where precipitation is seasonal in nature and zero values are common, there will be too many zero precipitation values in a particular season. In these climatic zones, the calculated SPI values at short time scales may not be normally distributed because of the highly skewed underlying precipitation distribution and because of the limitation of the fitted gamma distribution. This may be prone to large errors while simulating precipitation distributions in dry climates from small data samples.

B) The standardized precipitation evapotranspiration index (SPEI index). The SPEI drought index is based on the precipitation and potential evapotranspiration data. The information about the potential evapotranspiration temperature is mostly derived using the temperature data. The SPEI index is expressed using the differences between precipitation and potential evapotranspiration. Its calculation technically follows the derivation of SPI index; the only difference is that instead of the precipitation time series the time series of the above-mentioned differences are used. (Aula, 2009). The estimation of SPI and SPEI drought indices was made using the R package. (Beguería et al, 2003). The probability distribution of SPEI was expressed using the three-parameter log-logistic probability distribution and the SPI probability distribution was calculated using the Gamma distribution. The parameters were identified using the method of the maximum likelihood solutions.(Thom, 1966).

Fitting methods

The precipitation is being sorted from the smallest to the largest, after being sorted; it's fitted into a Gama distribution which is true, which means the cumulative distribution function. The cumulative distribution function is being transformed into the inverse of the Gaussian distribution.

The fitting procedure is as shown below.

Rainfall (R)

↓

Sorted R

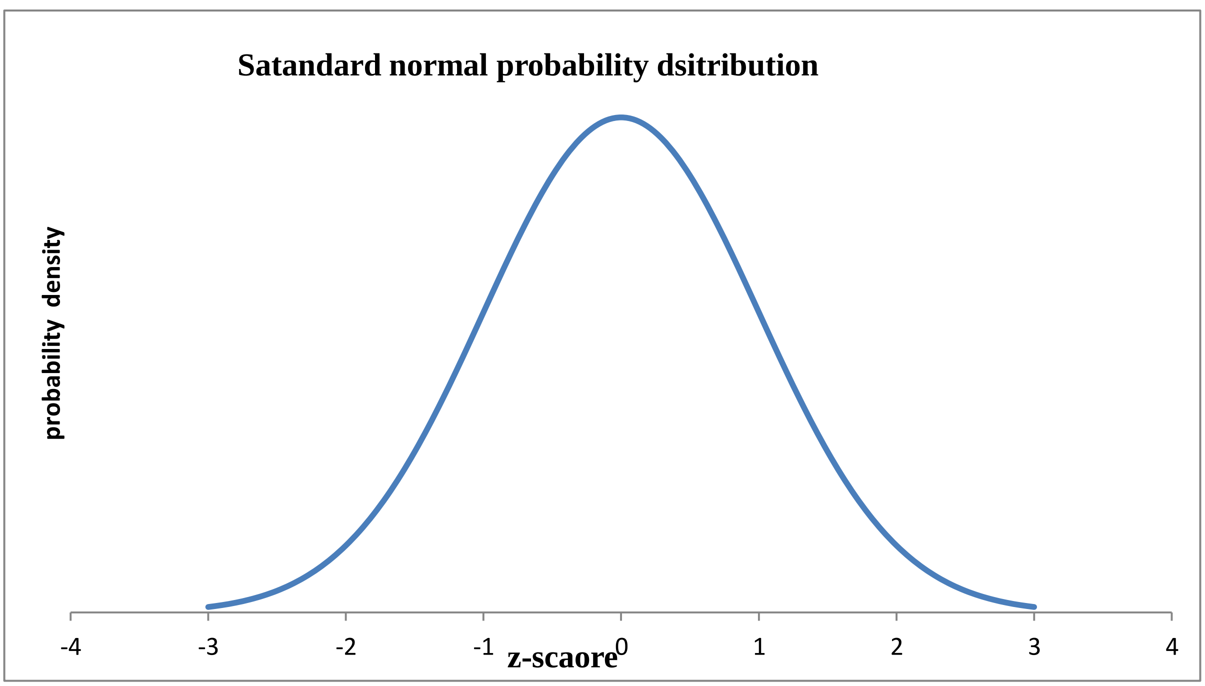
↓

GAMMADIST(R, alpha, beta, TRUE) = CDF

↓

Inverse of Gaussian distribution= NORMINV (CDF, mean=0, sd=1)

Figure 2.Standard normal probability distribution.



The figure 2.above shows a standardized normal probability distribution with mean 0 and standard deviation of 1.

The SPI indicates the extremity of droughts. The SPI values split the range into extremely dry ($SPI \leq -2$), severely dry ($-2 < SPI \leq -1.5$), moderately dry ($-1.5 < SPI \leq -1$), and near neutral conditions ($-1.0 < SPI \leq 1.0$) according to Cancelliere, et al, (2007).

CORRELATION

Correlation is a process by which the degree of association between samples of two variables is defined. The correlation coefficient is a mathematical definition of that association. It is, of course, possible to compute a correlation coefficient from any two sets of data. Furthermore, Correlation analysis measures the relationship between two items, for example, a security's price and an indicator. The resulting value (called the "correlation coefficient") shows if changes in one item (e.g., an indicator) will result in changes in the other item (e.g., the security's price).When comparing the correlation between two items, one item is called the "dependent" item and the other the "independent" item. The goal is to see if a change in the independent item (which is usually an indicator) will result in a change in the dependent item (usually a security's price). This information helps you understand an indicator's predictive abilities. The correlation coefficient can range between ±1.0 (plus or minus one). A high correlation coefficient (i.e., closer to plus or minus one) indicates that the dependent variable (e.g., the security's price) will usually change when the independent variable (e.g., an indicator) changes. The direction of the dependent variable's change depends on the sign of the coefficient. If the coefficient is a positive number, then the dependent variable will move in the same direction as the independent variable; if the coefficient is negative, then the dependent variable will move in the opposite direction of the independent variable. Also, correlation analysis can be use in two basic ways: to determine the predictive ability of an indicator and to determine the correlation between two securities.
(Reference link: http://www.metastock.com/customer/resources/taaz/?c=3&p=44)

Table 3.Correlation class, types and descriptions

Correlation class	Types	Description
+1.0	Perfect positive correlation	means that changes in the independent item will result in an identical change in the dependent item
-1.0	Perfect negative correlation	Means that changes in the independent item will result in an identical change in the dependent item, but the change will be in the opposite direction.
less than ±0.10	Weak correlation	Suggests that the relationship between two items is weak or non-existent.
0	Zero correlation	Means there is no correlation

Table 3.table shows the various correlation classes and the meaning for better understanding.

Types of correlation

There are basically three types of correlation which are as follows**:**

A) Pearson r correlation: Pearson r correlation is the most widely used correlation statistic to measure the degree of the relationship between linearly related variables.

B) **Kendall rank correlation**:- Kendall rank correlation is a nonparametric test that measures the strength of dependence between two variables.

C) **Spearman rank correlation**: Spearman rank correlation is a nonparametric test that is used to measure the degree of association between two variables. It was developed by Spearman, thus it is called the Spearman rank correlation.

Chapter 4

RESULTS AND ANALYSIS

Result

Estimation of SPI and SPEI

The SPI was estimated using different distributions and fitting methods, which are as follows, log-Logistic, Gamma and Pearson III distribution and ub-pwm, max-lik as fitting methods respectively. The SPI was being estimated from 1948 to 2003 for all the 8 basins. Appendix 1 to 5 show details procedure on how the SPI was being calculated for this research.This process is being repeated for the 8 different basins since we are using different data for each basin.

STEP 1

A) Calculations of total monthly precipitations for basins from 1948-2003.

After the monthly precipitation was being calculated, a scatter plot of the calculated precipitation was being plotted for all the basins as shown in **appendix 1**.

The curves below show the scatter plots for monthly rainfall variations from 1948-2003 for the eight basins.

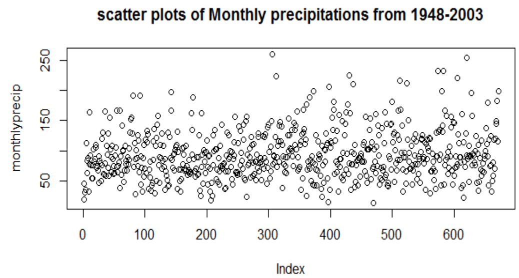


Figure 3.Scatter plots for monthly precipitations.

Figure 3.shows the Scatter plots for monthly precipitations for basin 1138000 from 1948-2003.

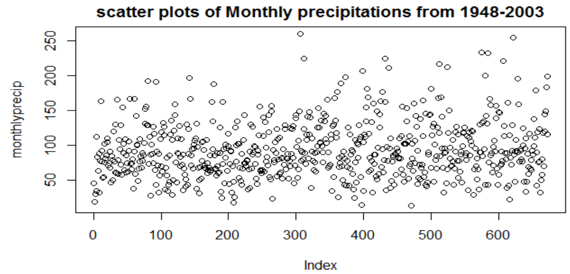


Figure 4.Scatter plots for monthly precipitations.

Figure 4.shows the Scatter plots for monthly precipitations for basin 3213000 from 1948-2003.

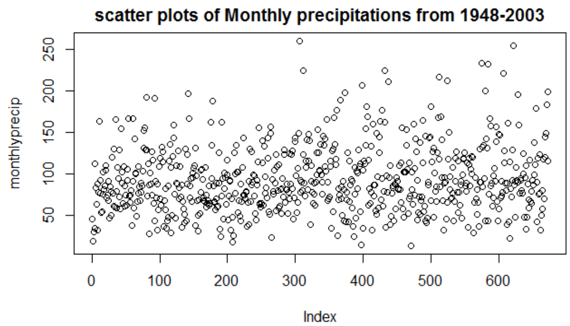


Figure 5.Scatter plots for monthly precipitations.

Figure 5.shows the Scatter plots for monthly precipitations for basin 4198000 from 1948-2003.

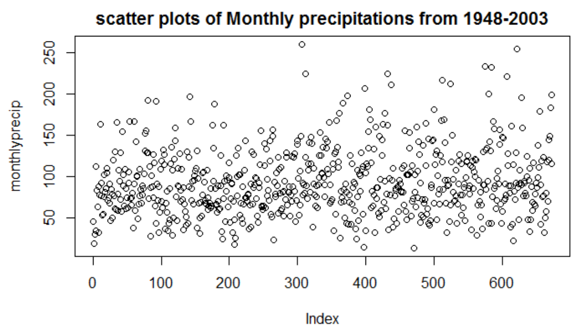


Figure 6.Scatter plots for monthly precipitations.

Figure 6.shows the Scatter plots for monthly precipitations for basin 6191500 from 1948-2003.

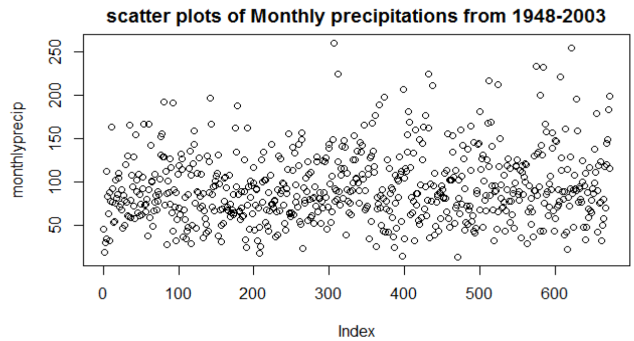


Figure 7.Scatter plots for monthly precipitations.

Figure 7.shows the Scatter plots for monthly precipitations for basin 8032000 from 1948-2003.

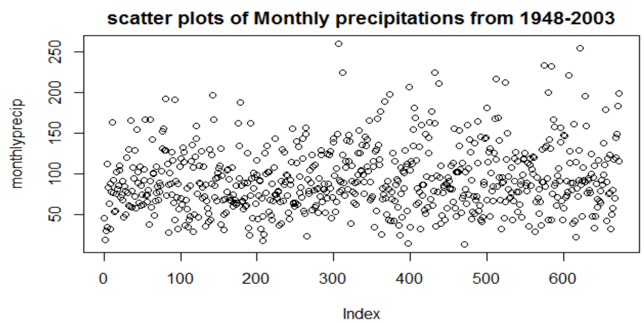


Figure 8.Scatter plots for monthly precipitations.

Figure 8.shows the Scatter plots for monthly precipitations for basin 12413500 from 1948-2003.

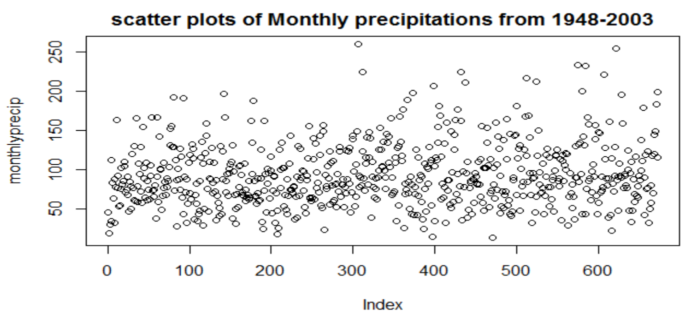


Figure 9.Scatter plots for monthly precipitations.

Figure 9.shows the Scatter plots for monthly precipitations for basin 3010500 from 1948-2003.

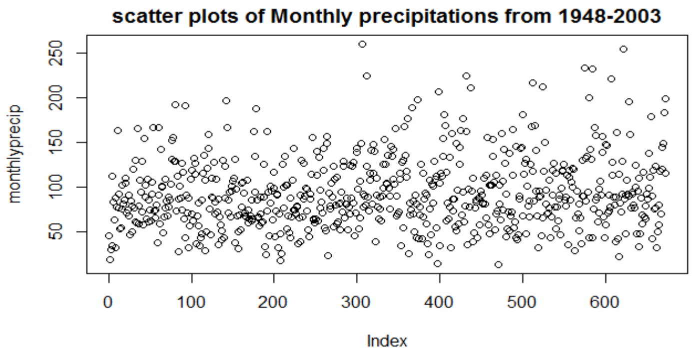


Figure 10.Scatter plots for monthly precipitations.

The figure 10.above shows the Scatter plots for monthly precipitations for basin 3010500 from 1948-2003.

STEP 2

B) Calculations of Empirical probabilities.

The calculations of empirical probabilities are as shown in appendix 2.

STEP 3

C) Estimation of alpha and beta parameters of the gamma probability density function.

Maximum likelihood estimation of the parameter of Gamma distribution was used in this research for the estimation of parameters for Gamma distribution and it is as shown in Appendix 3.

STEP 4

D) Calculation of theoretical probabilities from Gamma distribution for each R[i]

The calculation is as shown in appendix 4.

After the empirical and theoretical probabilities were being calculated, I then plot a curve between the two variables to see how they vary with each other.

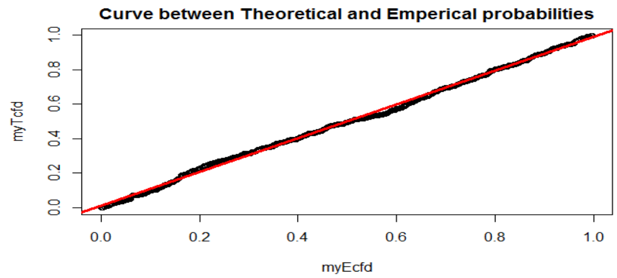


Figure 11.Regression curve between theoretical and Empirical probabilities

Figure 11.shows the Regression curve between theoretical and Empirical probabilities for basin 1138000 from 1948-2003.

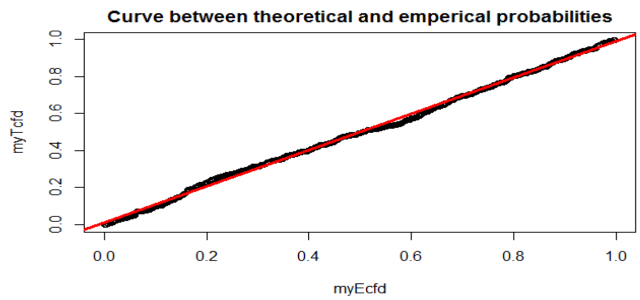


Figure 12.Regression curve between theoretical and Empirical probabilities

Figure 12.shows the Regression curve between theoretical and Empirical probabilities for basin 3213000 from 1948-2003.

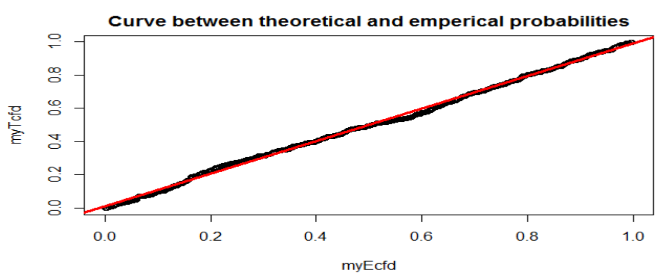


Figure 13.Regression curve between theoretical and Empirical probabilities

Figure 13.shows the Regression curve between theoretical and Empirical probabilities for basin 4198000 from 1948-2003.

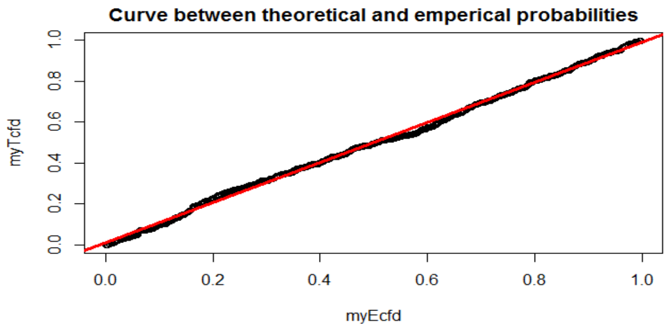


Figure 14.Regression curve between theoretical and Empirical probabilities

Figure 14.shows the Regression curve between theoretical and Empirical probabilities for basin 6191500 from 1948-2003.

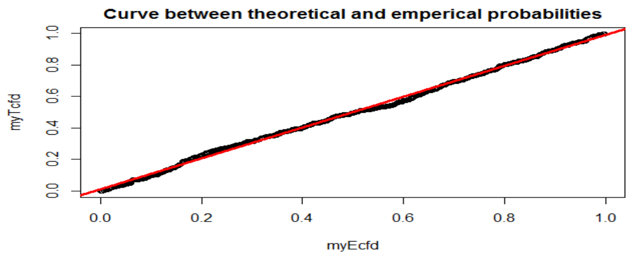


Figure 15.Regression curve between theoretical and Empirical probabilities

Figure 15.shows the Regression curve between theoretical and Empirical probabilities for basin 8032000 from 1948-2003.

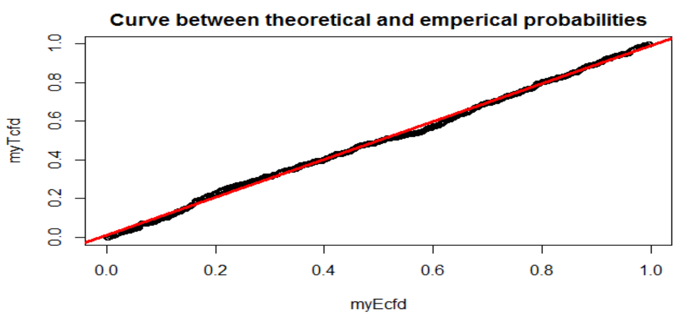


Figure 16.Regression curve between theoretical and Empirical probabilities

Figure 16.shows the Regression curve between theoretical and Empirical probabilities for basin 12413500 from 1948-2003.

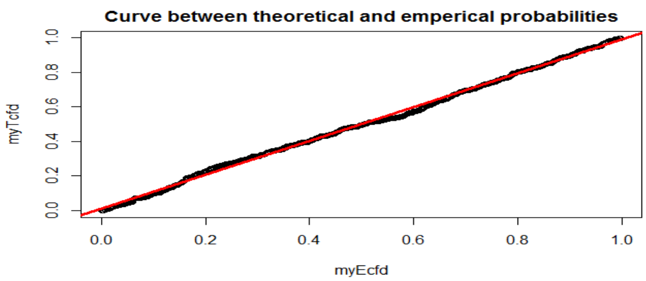


Figure 17.Regression curve between theoretical and Empirical probabilities

Figure 17.shows the Regression curve between theoretical and Empirical probabilities for basin 3010500 from 1948-2003.

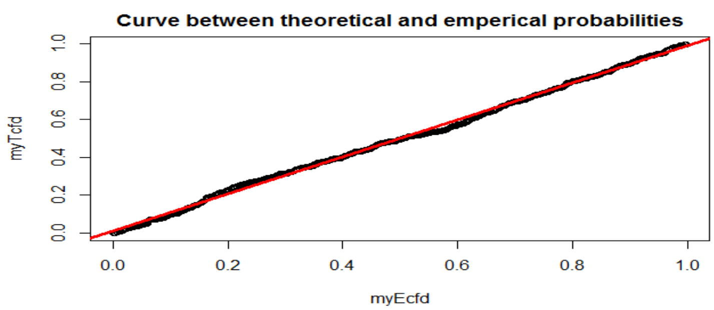


Figure 18.Regression curve between theoretical and Empirical probabilities

Figure 18.shows the Regression curve between theoretical and Empirical probabilities for basin 14321000 from 1948-2003.

We can view from the linear regression curves for all the basins that there is a strong relationship between the empirical and theoretical probabilities that is an increase in one will lead to an increase in the other and a decrease in one will lead to a decrease in the other.

STEP 5

Calculation of SPI

The calculation of SPI is as shown in appendix 5.

The procedures are clearly shown on the appendixes mention above. In addition to the above, i further used the SPEI package to calculate the SPI and SPEI using different distribution and fitting methods as mention above earlier.

According to Cancelliere, et al, (2007), the SPI values split the range as shown in the table below.

Table 4.SPI range and conditions

CONDITIONS	SPI RANGE
Extremely dry	$SPI \leq -2$
Severely dry	$-2 < SPI \leq -1.5$
Severely dry	$-1.5 < SPI \leq -1$
near neutral conditions	$-1.0 < SPI \leq 1.0$

The table 4.Shows the range of SPI value and conditions.

SPI variations using different distribution and fitting methods

Each curve below carries a particular alphabet which indicates the probability distribution and the fitting methods used.

a) log-Logistic distribution', fit = 'ub-pwm
b) log-Logistic'=distribution, fit = 'max-lik
c) Distribution = 'Gamma', fit = 'ub-pwm',
d) Distribution = 'Gamma', fit = 'max-lik'
e) Distribution = 'PearsonIII', fit = 'ub-pwm
f) Distribution = 'PearsonIII', fit = 'max-lik

Figure 19.SPI for Basin 1138000

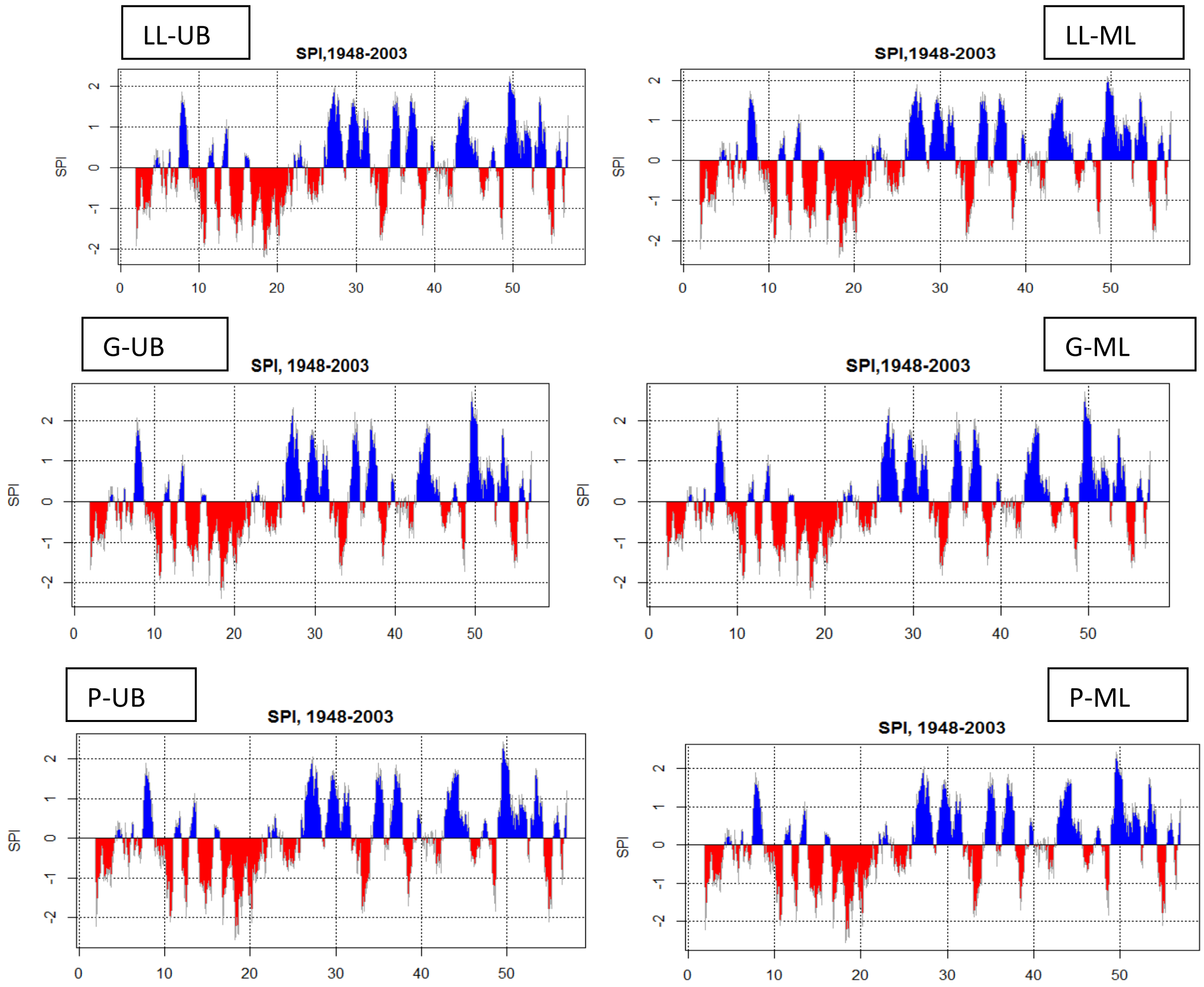


Figure 19.Shows SPI variations for basin 1138000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPI Index for basin 3213000

Figure 20.SPI for Basin 3213000

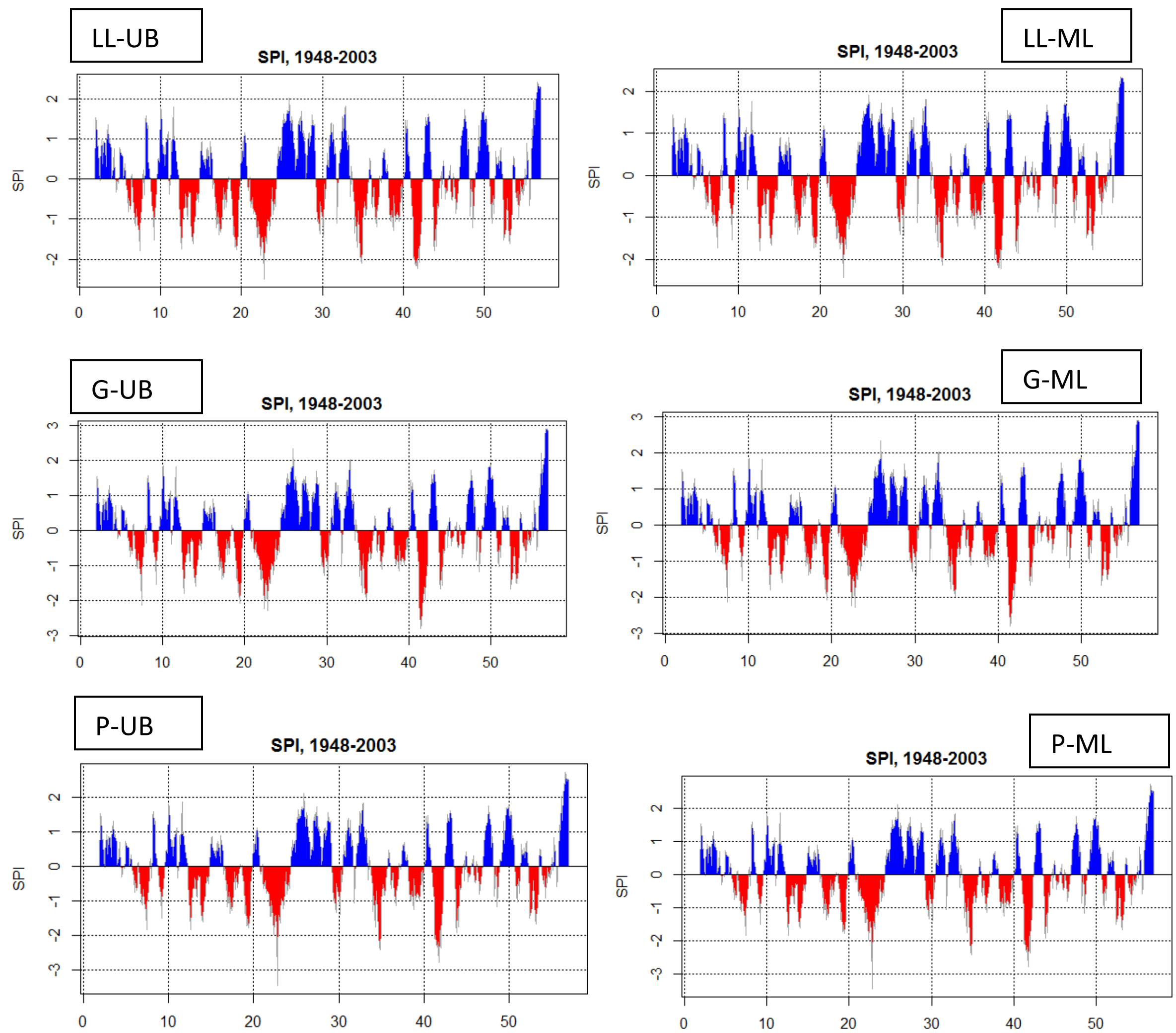


Figure 20.shows SPI variations for basin 3213000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPI Index for basin 4198000

Figure 21.SPI for Basin 4198000

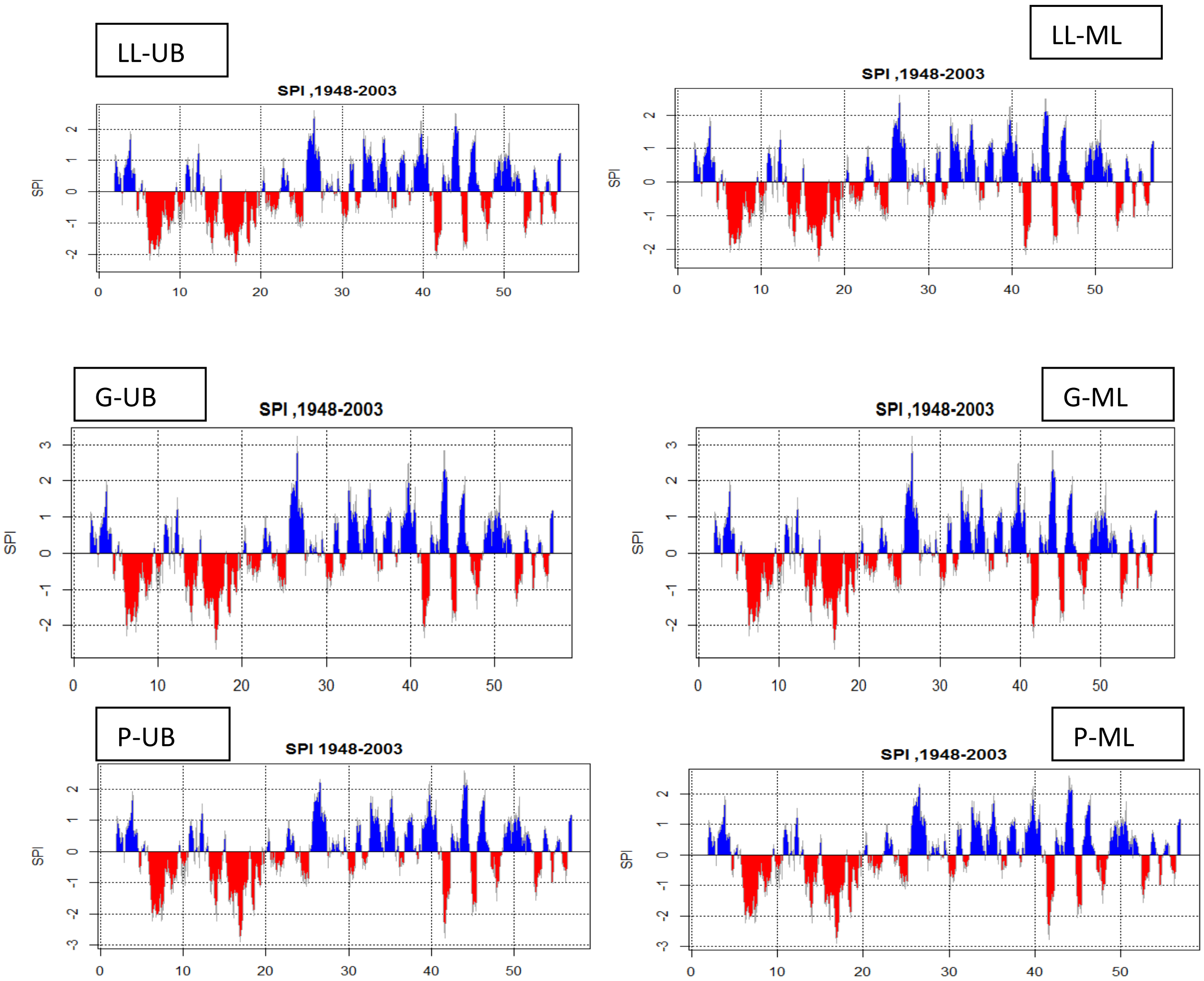


Figure 21.shows SPI variations for basin 4198000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPI Index for 6191500

Figure 22.SPI for Basin 6191500

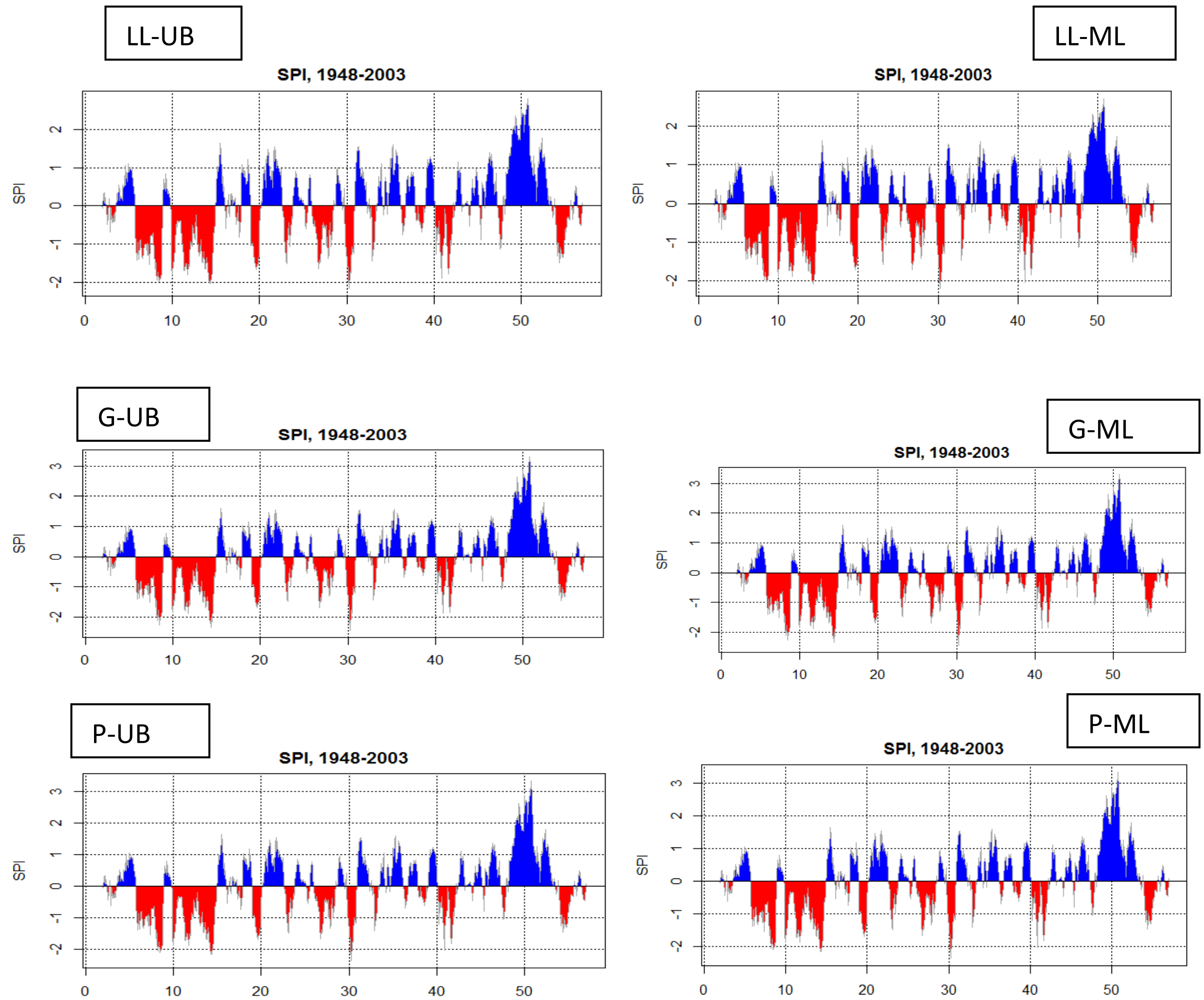


Figure 22.shows SPI variations for basin 6191504 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPI Index for basin 8032000

Figure 23.SPI for Basin 8032000

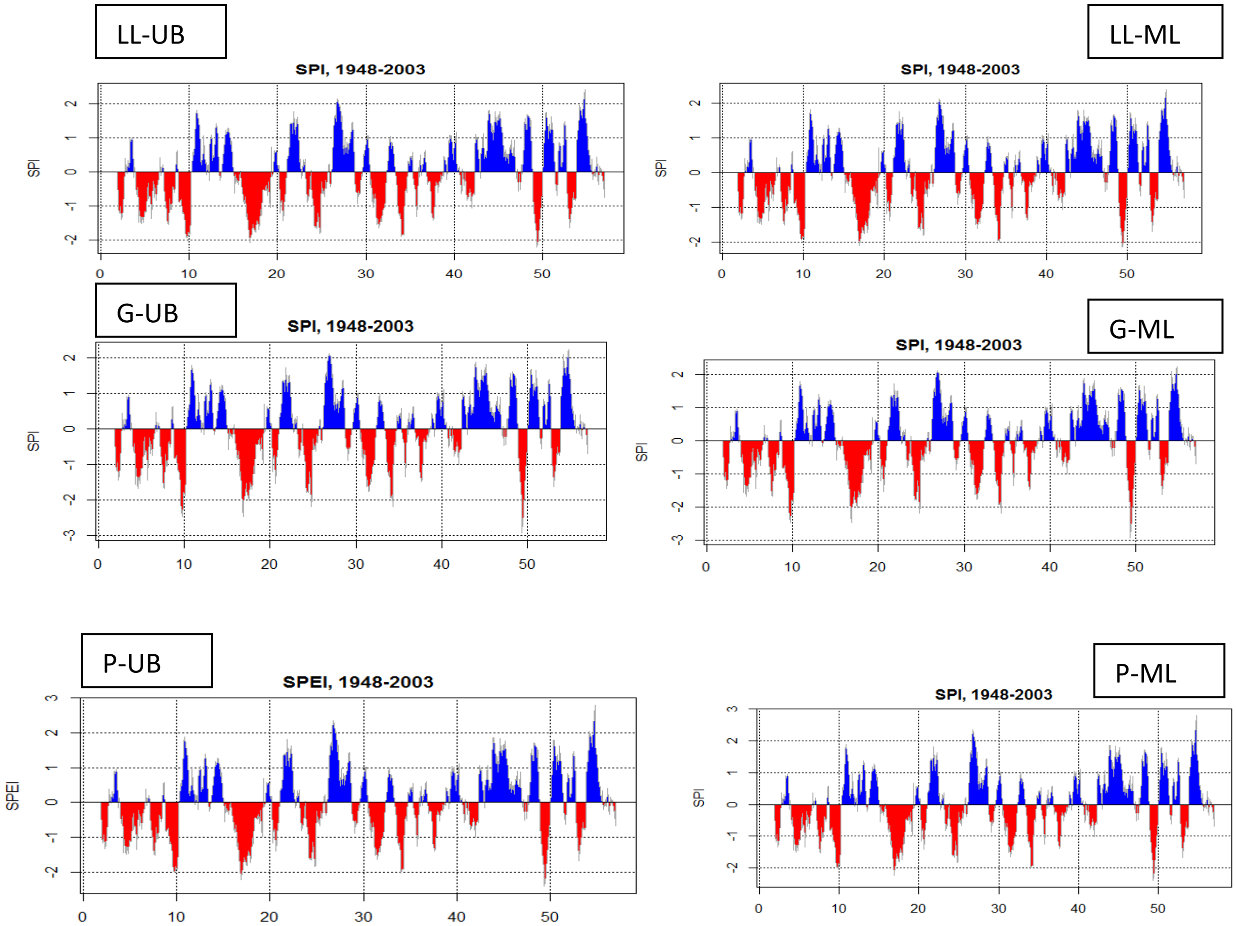


Figure 23.shows SPI variations for basin 8032000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPI Index for basin 12413500

Figure 24.SPI for Basin 12413500

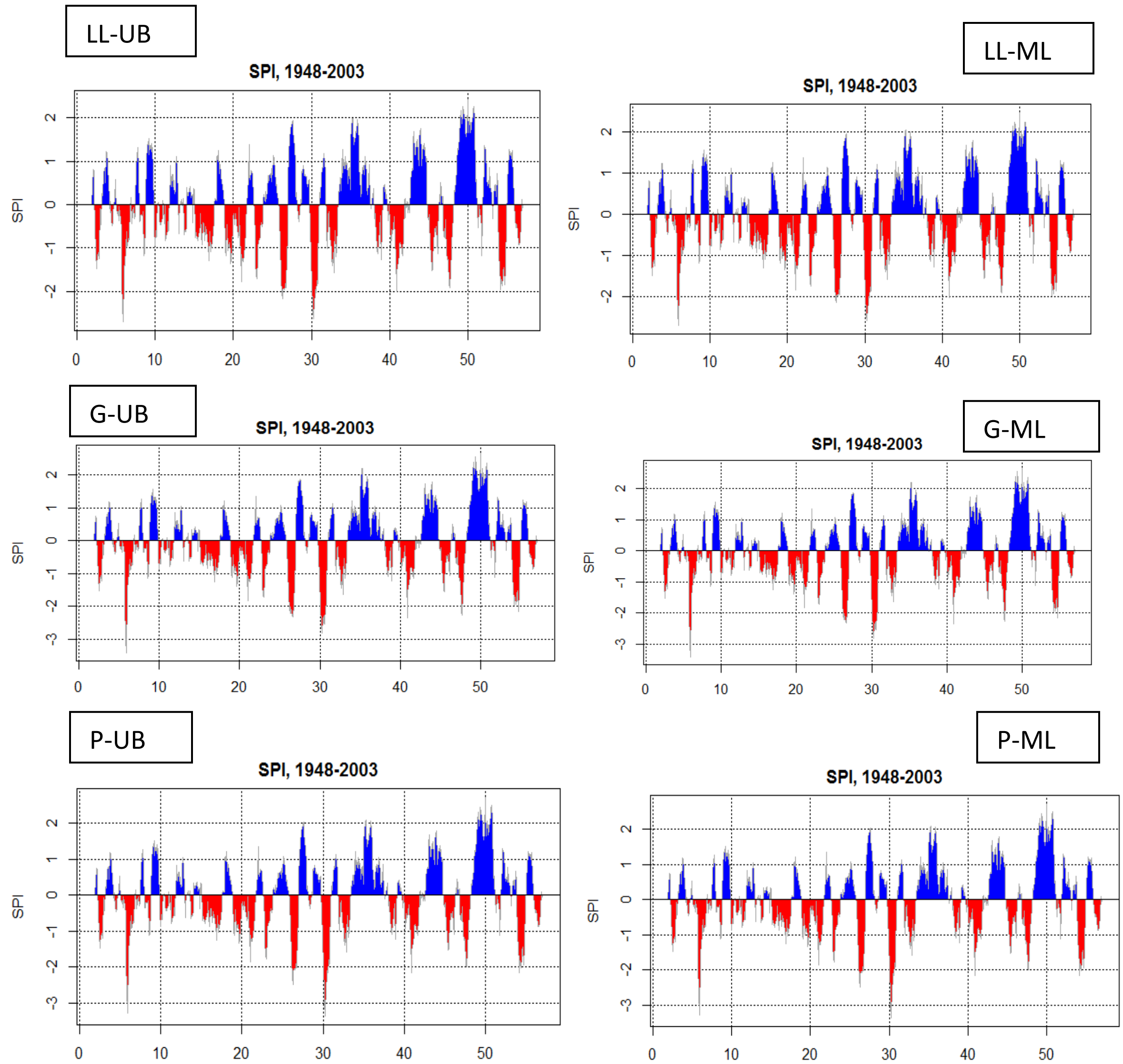
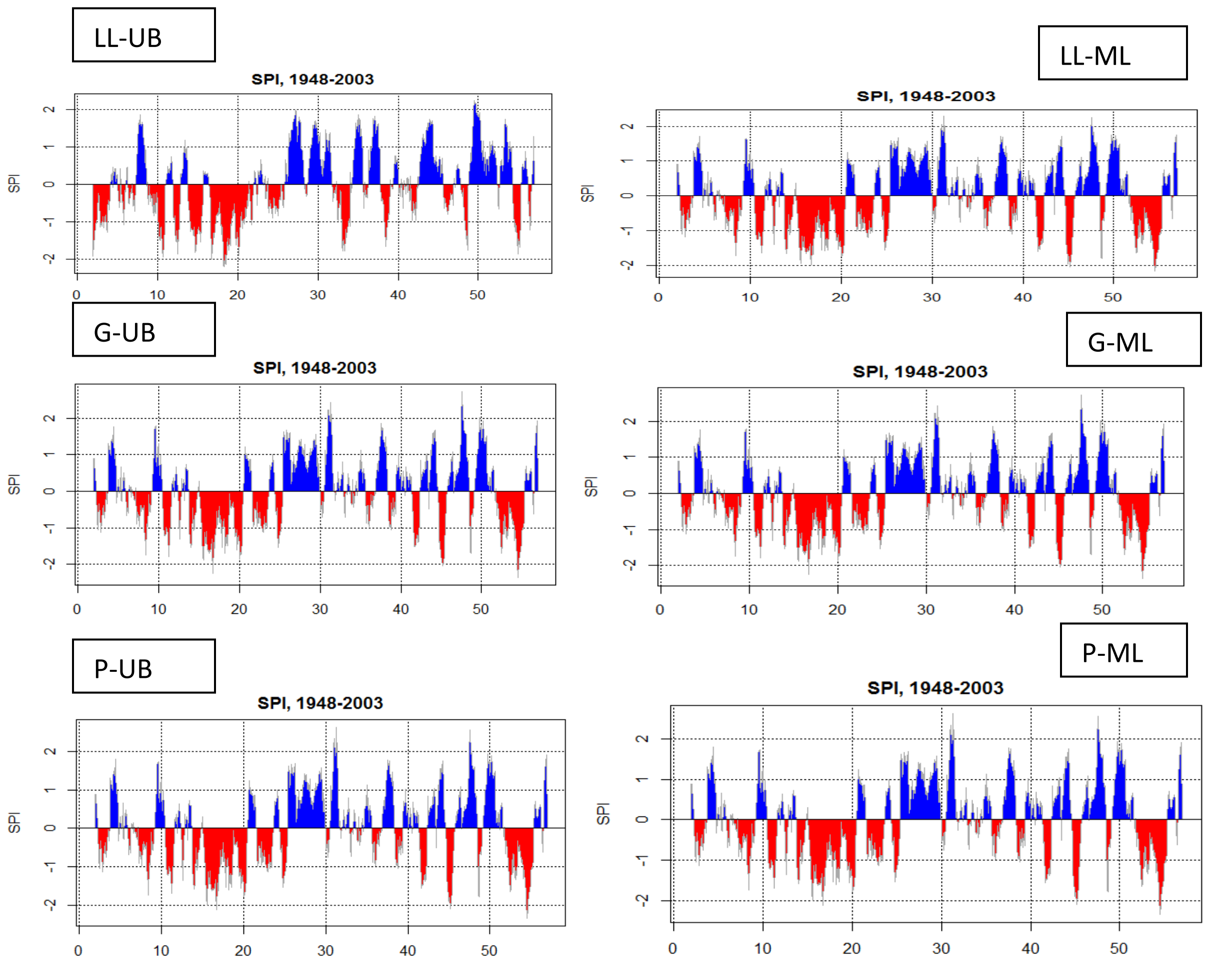


Figure 24.shows SPI variations for basin 12413500 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPI Index for basin 3010500

Figure 25.SPI for Basin 3010500



The figure 25.above shows SPI variations for basin 3010500 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPI Index for basin 14321000

Figure 26.SPI for Basin 14321000

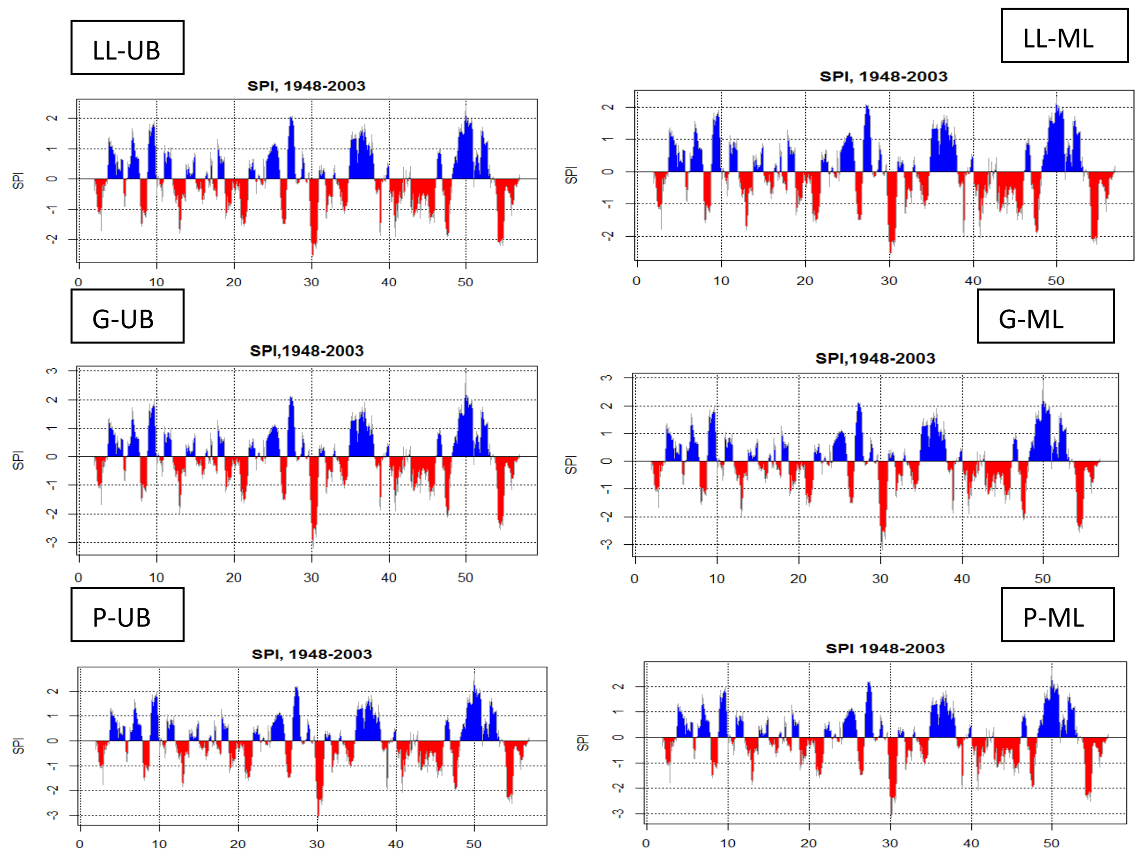


Figure 26.shows SPI variations for basin 14321000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPEI Index for basins

The SPEI calculation was done using different distributions and fitting methods, which are as follows, log-Logistic, Gamma and Pearson III distribution and ub-pwm, max-lik as fitting methods respectively. The SPEI was being estimated from 1948 to 2003 for all the 8 basins. Details procedure on how the SPEI was being calculated for this research is as shown in appendix 6, using the SPEI package.

STEP A

A) Calculations of total monthly PET for basins from 1948-2003.

The procedure for the calculation for PET is as shown in appendix 1.

STEP B

Calculation of SPEI

The procedure for the estimation of SPEI is the same as for SPI, the only difference is that in the space for precipitation i used the difference between precipitation and PET calculated.
It is as shown in appendix 7.

SPEI estimation using different distributions and fitting methods

Each curve below carries a particular alphabet which indicates the probability distribution and the fitting methods used.

a) log-Logistic distribution', fit = 'ub-pwm
b) log-Logistic'=distribution, fit = 'max-lik
c) Distribution = 'Gamma', fit = 'ub-pwm',
d) Distribution = 'Gamma', fit = 'max-lik'
e) Distribution = 'PearsonIII', fit = 'ub-pwm
f) Distribution = 'PearsonIII', fit = 'max-lik

Estimation of SPEI Index for Basin 1138000

Figure 27.SPEI for Basin 1138000

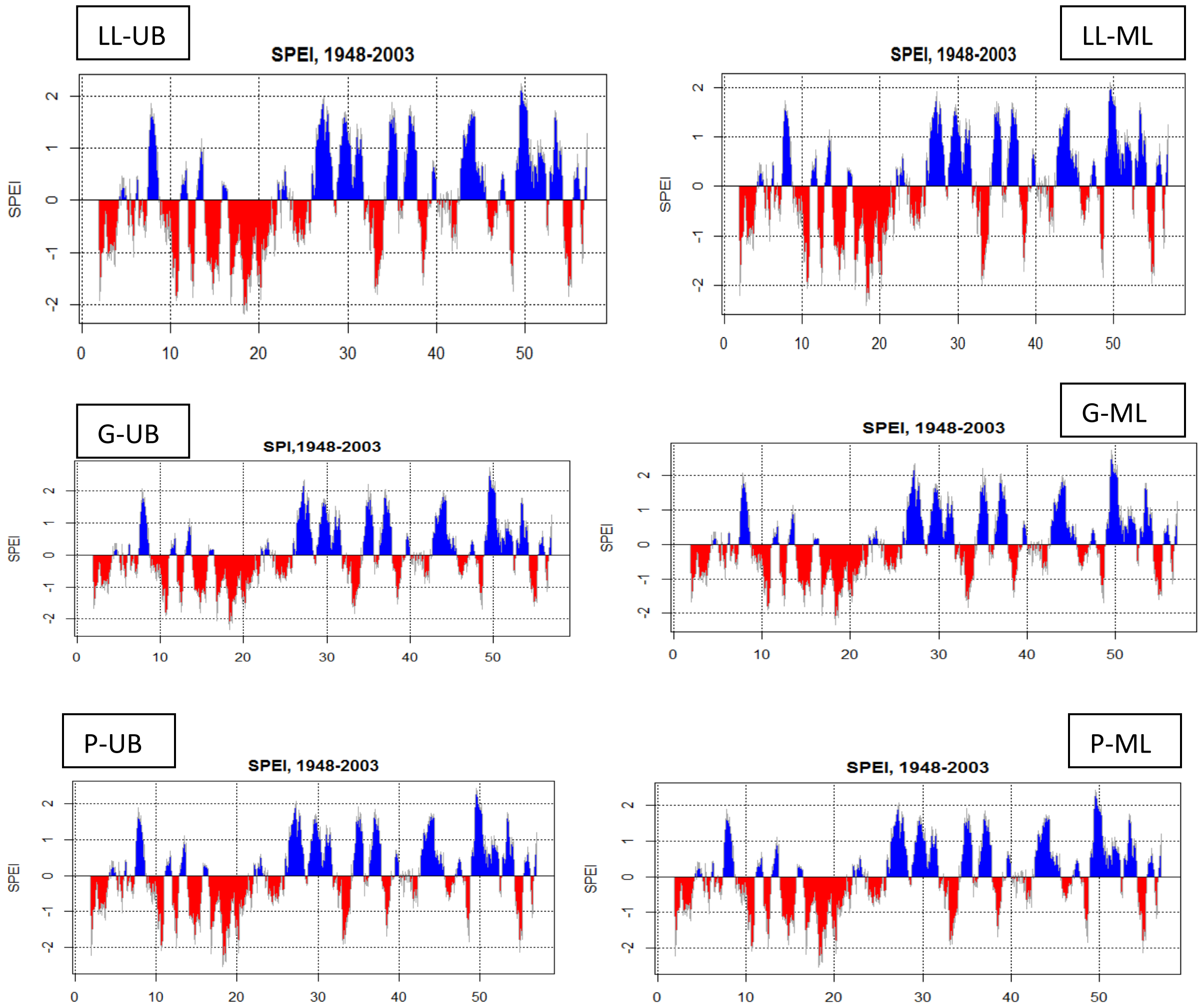
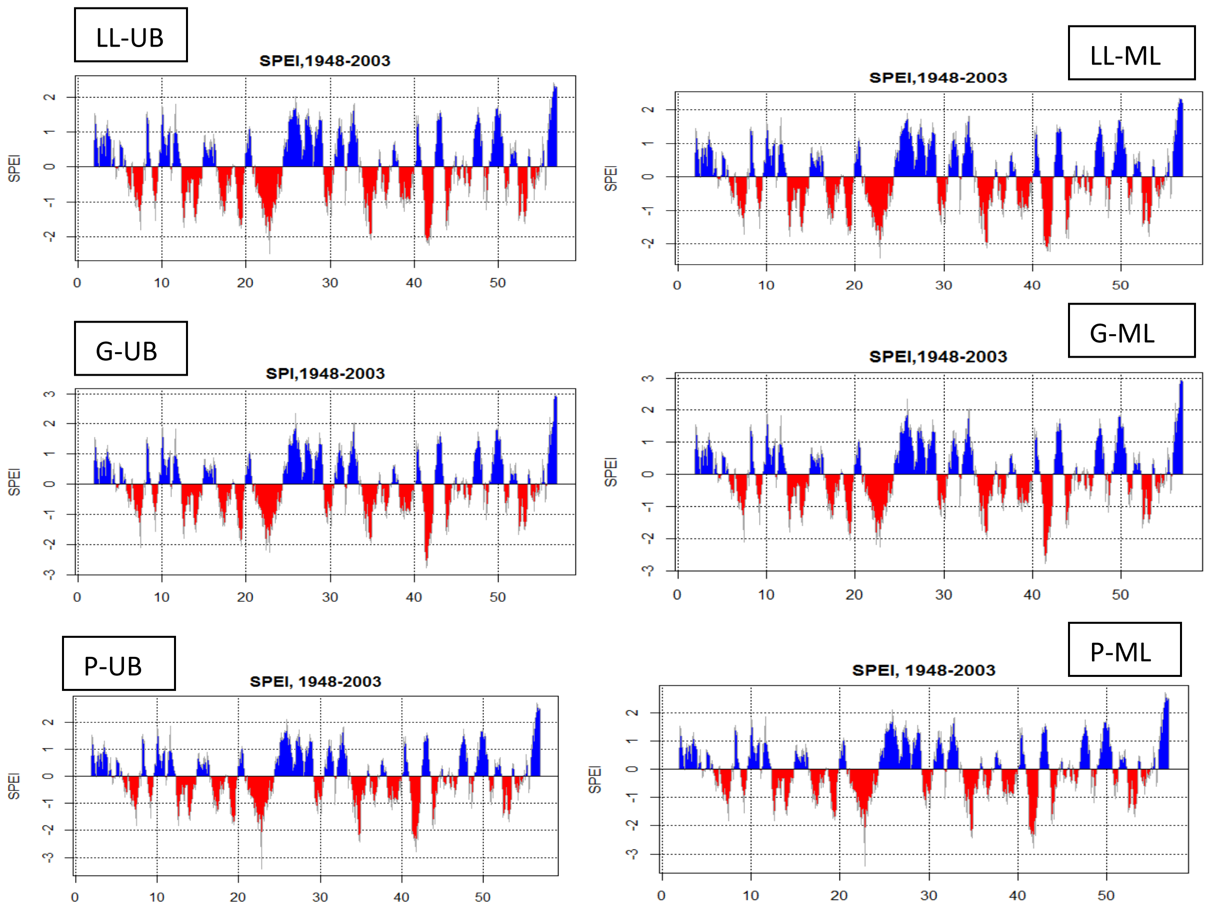


Figure 27.shows SPEI variations for basin 1138000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPEI Index for Basin 3213000

Figure 28.SPEI for Basin 3213000



The figure 28.shows SPEI variations for basin 3213000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPEI Index for Basin 6191504

Figure 29.SPEI for Basin 6191504

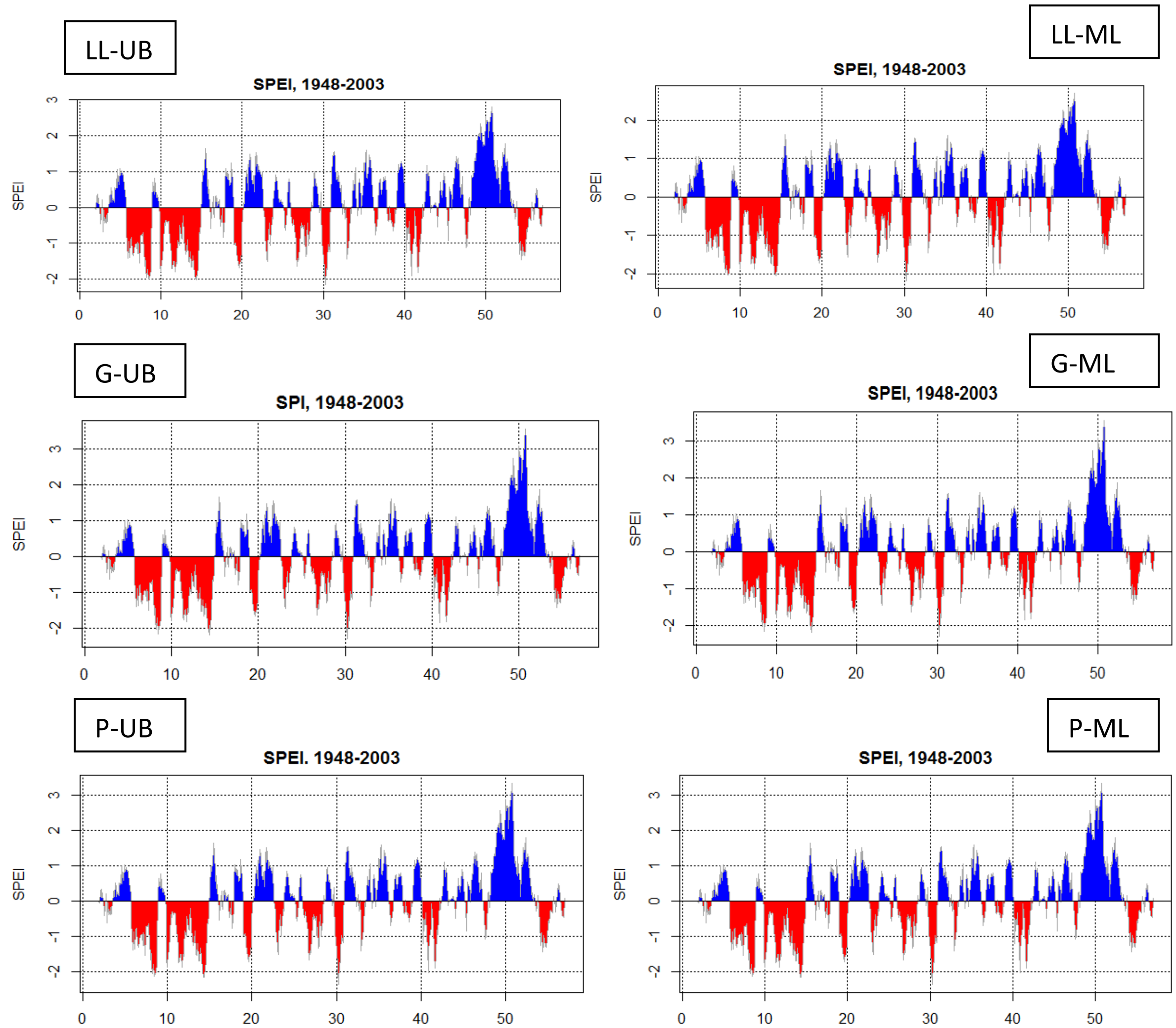


Figure 29.shows SPEI variations for basin 6191504 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPEI Index for Basin 8032000

Figure 30.SPEI for Basin 8032000

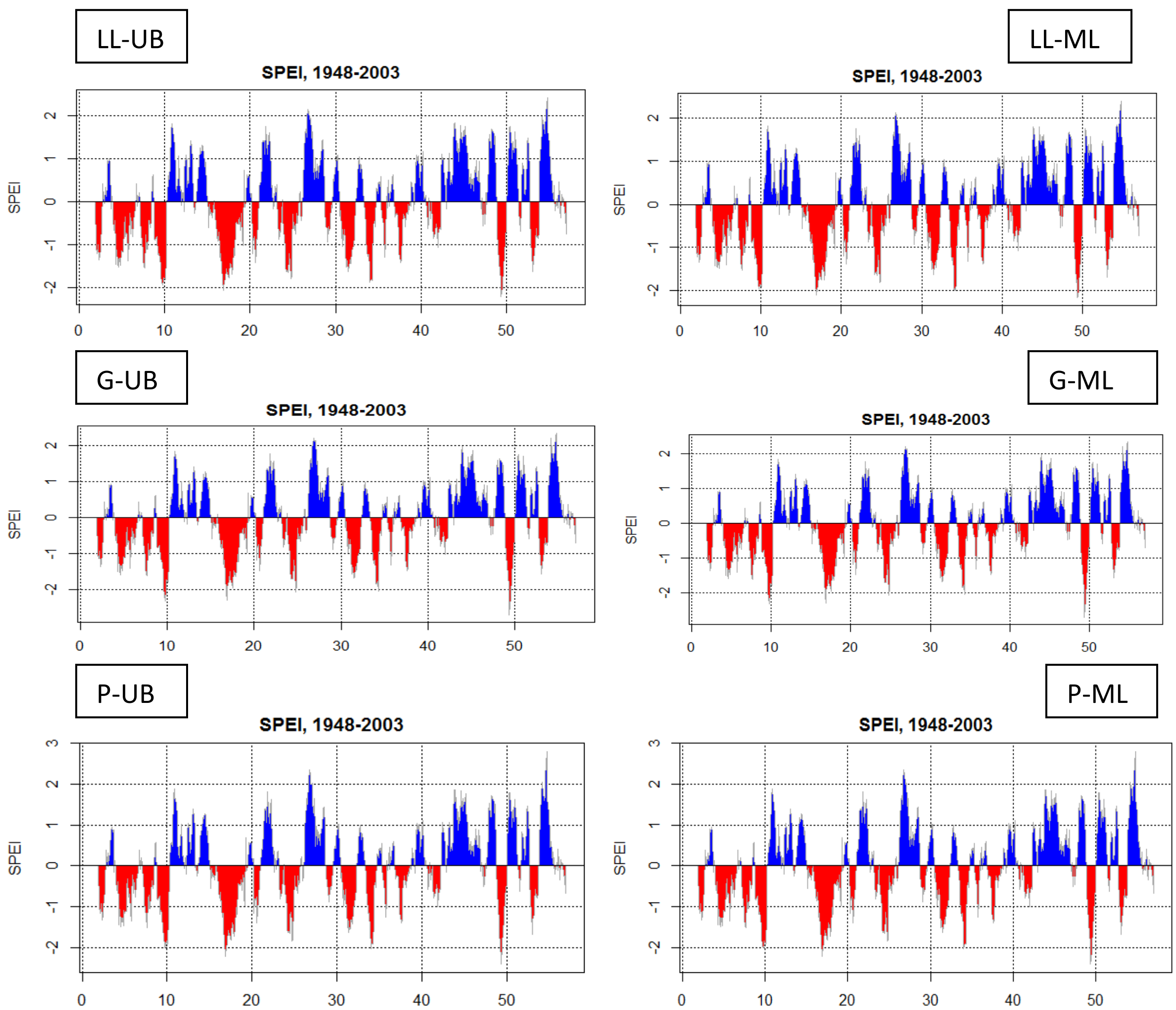


Figure 30.shows SPEI variations for basin 8032000 from 1948-2003 using the 3 distribution and two fitting methods mention above

Estimation of SPEI Index for Basin 12413500

Figure 31.SPEI for Basin 12413500

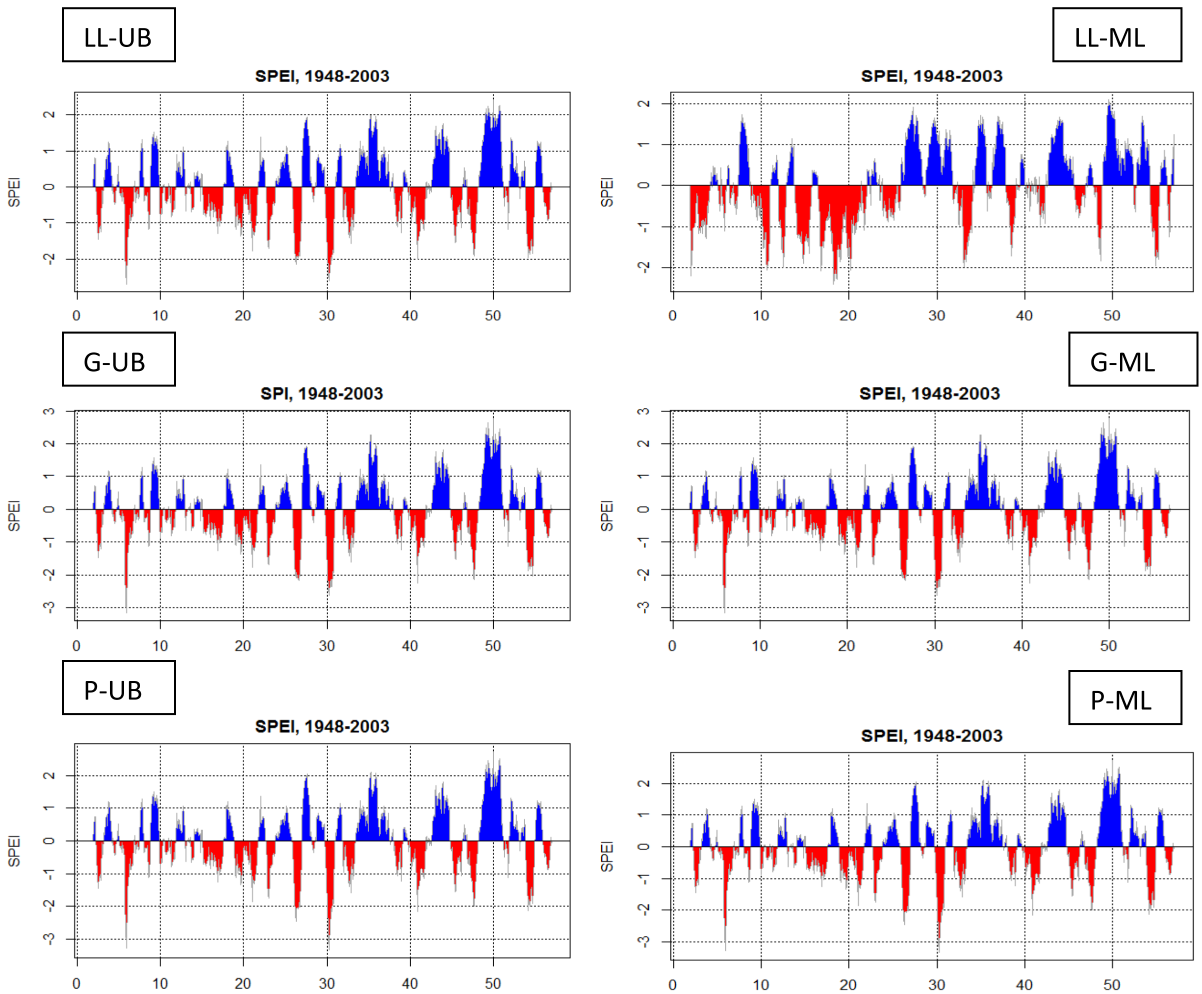


Figure 31.shows SPEI variations for basin 12413500 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPEI Index for Basin 3010500

Figure 32.SPEI for Basin 3010500

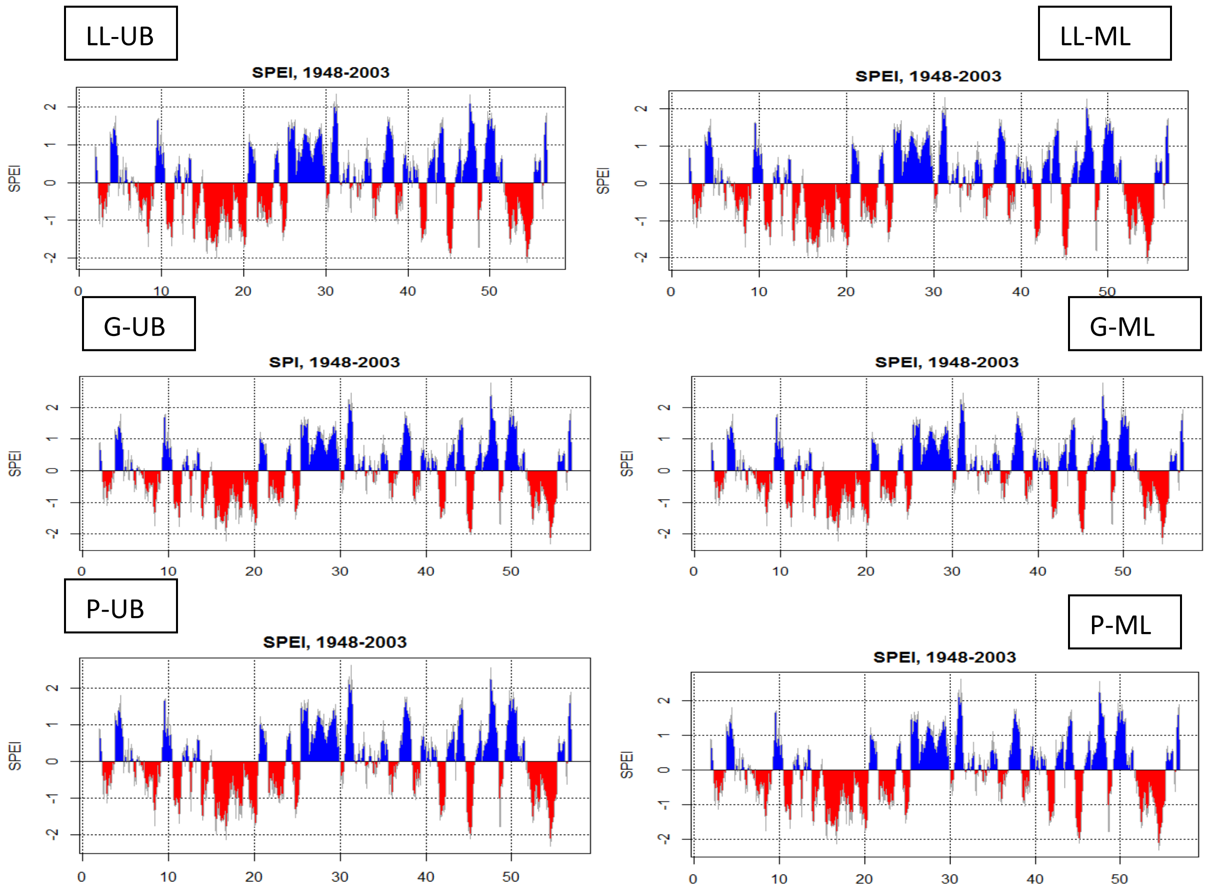


Figure 32.shows SPI variations for basin 3010500 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Estimation of SPEI Index for Basin 14321000

Figure 33.SPEI for Basin 14321000

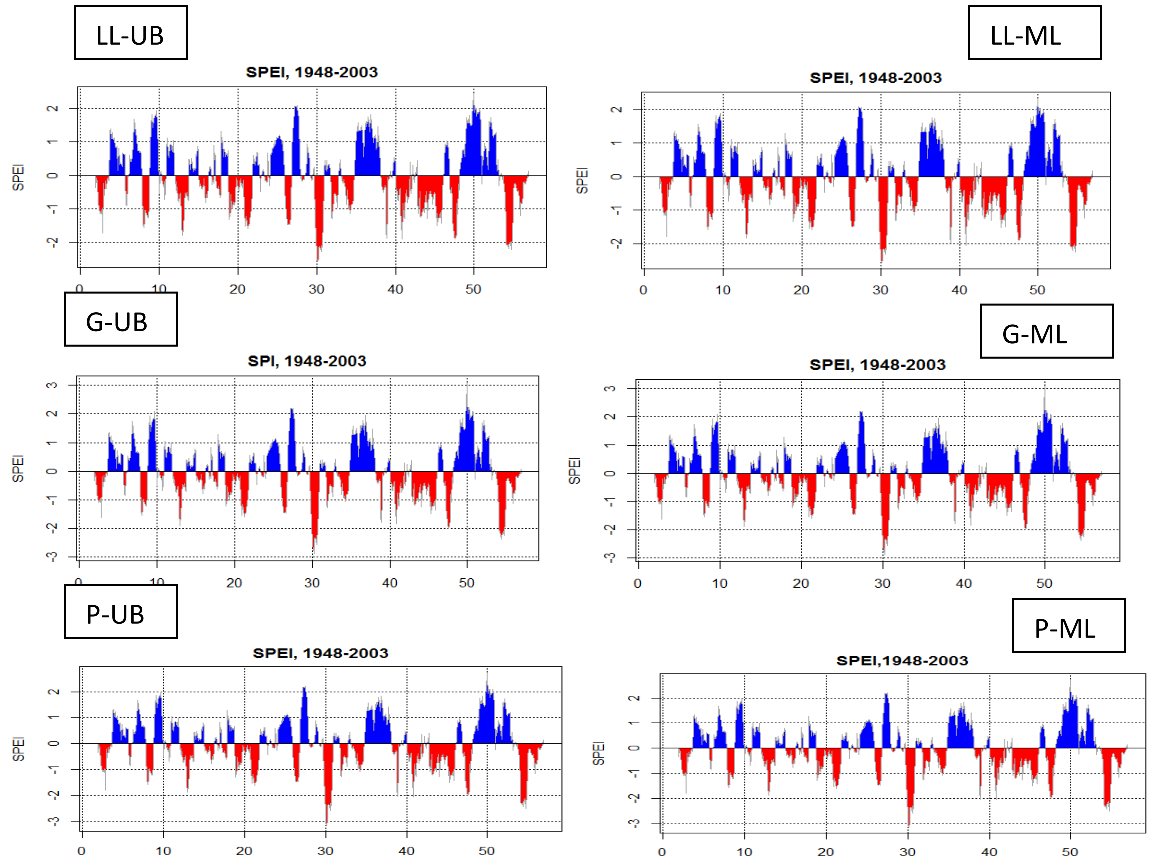


Figure 33.shows SPEI variations for basin 14321000 from 1948-2003 using the 3 distribution and two fitting methods mention above.

Table 5.Basin SPI and SPEI Range

USGS basin ID	SPI RANGE	SPEI RANGE
1138000	-2.559635, 2.708859	-2.530915, 2.736242
3213000	-3.446702, 2.897091	-3.425653, 2.946792
4198000	-2.886303, 3.235234	-2.746668, 3.282927
6191500	-2.441301, 3.330969	-2.361382, 3.557777
8032000	-2.918874, 2.805181	-2.692609, 2.806552
12413500	-3.418763 , 2.730426	-3.322684, 2.785730
3010500	-2.359584, 2.733998	-2.311879, 2.779391
14321000	-3.191820, 2.936448	-3.132554, 3.097943

The range of SPI and SPEI for each basin shows on Table 5.The lowest values for SPI was obtained from basin 14321000 and the highest values from basin 6191500.Also, the lowest SPEI values were obtained from basin 14321000 and highest values from basin 6191500.

ANALYSIS

CORRELATION ANALYSIS FOR BASIN

Pearson correlation coefficient;

$$R_{SPI=}\frac{COV\left(SPI_{B1,SPI_{B2}}\right)}{\delta SPI_{B1}\delta SPI_{B2}}$$

Where;

COV= is the covariance

$R_{SPI=}$Pearson's correlation coefficient

$\delta SPI_{B1} = standard\ deviation\ of\ B1$

$\delta SPI_{B2} \ = standard\ deviation\ of\ B2$

The SPEI correlation coefficient is also calculated in the same way as shown above where the SPI values are being replaced by SPEI values.

Table 6.SPI Correlation coefficients

Column1	B1	B2	B3	B4	B5	B6	B7	B8
B1	1	0.09761	0.28128	0.13314	0.07794	0.27993	0.41747	0.14909
B2	0.09761	1	0.29025	0.09934	-0.0134	0.03547	0.38864	0.09438
B3	0.28128	0.29025	1	0.2926	0.24437	0.25994	0.49954	0.1217
B4	0.13314	0.09934	0.2926	1	-0.1419	0.53729	0.23848	0.44101
B5	0.07794	-0.0134	0.24437	-0.1419	1	-0.1023	-0.0552	-0.202
B6	0.27993	0.03547	0.25994	0.53729	-0.1023	1	0.20922	0.67102
B7	0.41747	0.38864	0.49954	0.23848	-0.0552	0.20922	1	0.1782
B8	0.14909	0.09438	0.1217	0.44101	-0.202	0.67102	0.1782	1

Table 6.shows the general SPI correlations coefficients between basins, the largest coefficients was obtained from the correlation between B6/B4 which is 0.53729, the lowest coefficient was obtained from the correlation between B5/B2 which is -0.0134.

Table 7.SPI Distribution/fitting correlation coefficient

Column1	Log-ub	Log-max	Gam-ub	GAM-max	Pea-ub	Pea-max
Log-ub	1	0.999489	0.996318	0.996318	0.99789	0.99789
Log-max	0.999489	1	0.995218	0.995218	0.997699	0.997699
Gam-ub	0.996318	0.995218	1	1	0.997334	0.997334
Gam-max	0.996318	0.995218	1	1	0.997334	0.997334
Pea-ub	0.99789	0.997699	0.997334	0.997334	1	1
Pea-max	0.99789	0.997699	0.997334	0.997334	1	1

The distribution/fitting correlation coefficient is shown in table 7.The largest coefficient was obtained from the correlation between same distribution/fitting ie log-ub/log-ub and the list was obtained from the correlation between pea-max/Gam-ub.

Table 8.SPEI Correlation coefficients

Column1	**B11**	**B22**	**B33**	**B44**	**B55**	**B66**	**B77**	**B88**
B11	1	0.096183	0.27969	0.132889	0.079268	0.282084	0.415749	0.151586
B22	0.096183	1	0.289784	0.098022	-0.0107	0.035065	0.388775	0.094078
B33	0.27969	0.289784	1	0.291168	0.248293	0.259968	0.497955	0.12067
B44	0.132889	0.098022	0.291168	1	-0.13528	0.537706	0.236156	0.441047
B55	0.079268	-0.0107	0.248293	-0.13528	1	-0.09875	-0.0541	-0.19879
B66	0.282084	0.035065	0.259968	0.537706	-0.09875	1	0.209222	0.669587
B77	0.415749	0.388775	0.497955	0.236156	-0.0541	0.209222	1	0.178159
B88	0.151586	0.094078	0.12067	0.441047	-0.19879	0.669587	0.178159	1

Table 8 shows the general SPEI correlations coefficients between basins, the largest coefficients was obtained from the correlation between B66/B44 which is 0.537706, the lowest coefficient was obtained from the correlation between B55/B22 which is -0.0107.

Table 9.SPEI Distribution/fitting correlation coefficient

Column1	**log_ub1**	**log_max2**	**GAM_ub3**	**GAM_max4**	**pea_ub5**	**pea_max6**
log_ub1	1	0.9994849	0.996727596	0.996727596	0.99789584	0.997895844
log_max2	0.9994849	1	0.995313608	0.995313608	0.9977031	0.997703097
GAM_ub3	0.9967276	0.99531361	1	1	0.99749058	0.997490583
GAM_max4	0.9967276	0.99531361	1	1	0.99749058	0.997490583
pea_ub5	0.9978958	0.9977031	0.997490583	0.997490583	1	1
pea_max6	0.9978958	0.9977031	0.997490583	0.997490583	1	1

The distribution/fitting correlation coefficient is shown in table 9.The largest coefficient was obtained from the correlation between same distribution/fitting ie log-ub1/log-ub1 and the list was obtained from the correlation between pea-max6/Gam-ub3.

Chapter 5

DISCUSION AND CONCLUSION

DISCUSION

The use of different probability distributions affect the SPI values as the SPI is based on the fitting of a distribution to precipitation series. Some of the commonly applied distributions used in this research as mention earlier include: Gamma distribution (McKee et al., 1993; Edwards and McKee, 1997; Mishra and Singh, 2009); , Pearson Type III distribution (Guttman, 1999); and lognormal distribution, extreme value, and exponential distributions have been widely applied to simulations of precipitation distributions (Lloyd-Hughes and Saunders, 2002; Madsen et al., 1998; Todorovic and Woolhiser, 1976; Wu et al., 2007).Two types of problems arise: (i) When SPIs are calculated for long time scales (longer than 24 months) fitting a distribution might be biased due to the limitation in data length and it is true that when finer resolutions of spatial analysis need to be investigated, long data sets are not available in many catchments around the world. Lloyd-Hughes and Saunders (2002) and Sonmez et al. (2005) reported biased SPI values.(ii) For dry climates where precipitation is seasonal in nature and zero values are common, there will be too many zero precipitation values in a particular season. In these climatic zones, the calculated SPI values at short time scales may not be normally distributed because of the highly skewed underlying precipitation distribution and because of the limitation of the fitted gamma distribution. This may be prone to large errors while simulating precipitation distributions in dry climates from small data samples. In addition to the above, the table 4.shows you the SPI and SPEI range values for each basin and also reveals clear differences between SPI and SPEI range values calculated**.** We can also view in table 4 that majority of the range of SPI and SPEI values calculated are similar or slightly different, which implies that the probability distribution and fitting methods have little or no impact on the SPI and SPEI estimation.

CONCLUSIONS

I analyzed the estimation of two drought indices, SPEI and SPI, using three type of probability distribution and two types of fitting methods. The SPEI and SPI estimation was based on the data obtained from the period 1948–2003 from eight basins in the United States. The analyzed data were collected under MOPEX framework.

When evaluating the estimation of SPI and SPEI, the results reveals that probability distribution and fitting methods have little or no significant effects on the estimation process of the drought indices estimated.

Furthermore, when comparing the correlation between basins found out that the correlation coefficient between basins is weak or non-existent.

In addition to the above, the correlation between distribution and fitting methods pairs is a perfect positive correlation which means that changes in the independent item will result in an identical change in the dependent item.

REFERENCES

Dai A. Drought under global warming: a review. Wiley Interdisciplinary Reviews: Climate Change. 2011;2:45–65

Mishra A. K., Singh V. P. Drought modeling-a review. Journal of Hydrology. 2011;403(1-2):157–175.

Dai A.Increasing drought under global warming in observations and models. Nature Climate Change. 2013;3(1):52–58.

Ntale H. K., Gan T. Y. Drought indices and their application to East Africa. International Journal of Climatology. 2003;23(11):1335–1357.

Haslinger K., Koffler D., Schöner W., Laaha G. Exploring the link between meteorological drought and streamflow: effects of climate-catchment interaction. Water Resources Research. 2014;50(3):2468–2487.

Hayes M. J., Svoboda M. D., Wilhite D. A., Vanyarkho O. V. Monitoring the 1996 drought using the standardized precipitation index. Bulletin of the American Meteorological Society. 1999;80(3):429–438.

Cancelliere A., Mauro G. D., Bonaccorso B., Rossi G. Drought forecasting using the standardized precipitation index. Water Resources Management. 2007;21(5):801–819

Vicente-Serrano S. M., Beguería S., López-Moreno J. I. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of Climate. 2010;23(7):1696–1718.

Beguería S., Vicente-Serrano S. M., Reig F., Latorre B. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. International Journal of Climatology. 2014;34(10):3001–3023.

Belayneh A., Adamowski J., Khalil B., Ozga-Zielinski B. Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural networks and wavelet support vector regression models. Journal of Hydrology. 2014;508:418–429.

Hayes M. J., Svoboda M. D., Wilhite D. A., Vanyarkho O. V. Monitoring the 1996 drought using the standardized precipitation index. Bulletin of the American Meteorological Society. 1999;80(3):429–438. doi: 10.1175/1520-

Guttman N. B. Comparing the palmer drought index and the standardized precipitation index. Journal of the American Water Resources Association. 1998;34(1):113–121

Vicente-Serrano S. M., Beguería S., López-Moreno J. I. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of Climate. 2010;23(7):1696–1718.

Beguería S., Vicente-Serrano S. M., Reig F., Latorre B. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. International Journal of Climatology. 2014;34(10):3001–3023.

Beguería S., Vicente-Serrano S. M. SPEI: Calculation of the Standardised Precipitation—Evapotranspiration Index. R package version 1.6.

Vicente-Serrano S. M., Beguería S., López-Moreno J. I. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of Climate. 2010;23(7):1696–1718.

Beguería S., Vicente-Serrano S. M., Reig F., Latorre B. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring.International Journal of Climatology. 2014;34(10):3001–3023.

Guttman N. B. Comparing the palmer drought index and the standardized precipitation index. Journal of the American Water Resources Association. 1998;34(1):113–121.

Cancelliere A., Mauro G. D., Bonaccorso B., Rossi G. Drought forecasting using the standardized precipitation index.Water Resources Management. 2007;21(5):801–819.

Duan Q., Schaake J., Andréassian V., et al. Model Parameter Estimation Experiment (MOPEX): an overview of science strategy and major results from the second and third workshops. Journal of Hydrology. 2006;320(1-2):3–17.

Schaake J., Duan Q., Andréassian V., Franks S., Hall A., Leavesley G. The model parameter estimation experiment (MOPEX) Journal of Hydrology. 2006;320(1-2):1–2.

S.M. Vicente-Serrano, S. Beguería, J.I. López-Moreno. 2010. A Multi-scalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index – SPEI. Journal of Climate 23: 1696, DOI: 10.1175/2009JCLI2909.1.

Andreadis, K.M., Lettenmaier, D.P., 2006.Trends in 20th-century drought over the continental United States. Geophys. Res. Lett. 33, L10403. doi:10.1029/ 2006GL025711.

Aswathanarayana, U., 2001. Water Resources Management and the Environment.Balkema, Rotterdam, The Netherlands.

Riebsame, W.E., Changnon, S.A., Karl, T.R., 1990. Drought and Natural Resource Management in the United States: Impacts and Implications of the 1987–1989 Drought, Westview Press, p. 174.

Webster, K.E., Kratz, T.M., Bowser, C.J., Adagnuson, J.J., 1996.The influence of landscape position on lake chemical responses to drought in Northern Wisconsin. Limnol. Oceanogr. 41 (5), 977–984.

Clark, P.U., Alley, R.B., Pollard, D., 1999. Northern hemisphere ice-sheet influences on global climate change. Science 286, 1104–1111.

Gleick, P.H., 1987. Regional hydrologic consequences of increases in atmospheric CO2 and other trace gasses. Clim. Change 10, 137–161.

Panagoulia, D., 1992. Impact of GISS-modelled climate changes on catchment hydrology. Hydrol. Sci. J. 37, 141–163.

Szep, I.J., Mika, J., Dunkel, Z., 2005. Palmer drought severity index as soil moisture indicator: physical interpretation, statistical behaviour, and relation to global climate. Phys. Chem. Earth 30, 231–243.

Bruce, J.P., 1994.Natural disaster reduction and global change . Bull. Am. Meteorol. Soc. 75, 1831–1835.

Downing, T.E., Bakker, K., 2000. Drought discourse and vulnerability. In: Wilhite, D.A. (Ed.), Drought: A Global Assessment, Natural Hazards and Disasters Series. Routledge Publishers, UK.

Zeng, N., 2003.Drought in the Sahel. Science 302, 999–1000

Batterbury, S.P.J., Warren, A., 2001. The African Sahel 25 years After the Great Drought: Assessing Progress and Moving Towards New Agendas and approaches. Global Environmental Change, pp. 1–8.

Wilhite, D.A., Glantz, M.H., 1985.Understanding the drought phenomenon: the role of definitions. Water Int. 10, 111–120.

American Meteorological Society (AMS), 2004.Statement on meteorological drought. Bull. Am. Meteorol. Soc. 85, 771–773.

Pinkeye, S., 1966. Conditional Probabilities of Occurrence of Wet and Dry Years Over a Large Continental Area. Hydrol.Paper 12, Colorado State University, Fort Collins, Colorado.

Santos, M.A., 1983. Regional droughts: a stochastic characterization. J. Hydrol. 66, 183–211.

Chang, T.J., 1991.Investigation of precipitation droughts by use of kriging method. J. Irrig. Drain. Engrg., ASCE 117 (6), 935–943.

Chang, T.J., Kleopa, X.A., 1991.A proposed method for drought monitoring. Water Resour. Bull. 27, 275–281

Eltahir, E.A.B., 1992.Drought frequency analysis in Central and Western Sudan. Hydrological Sci. J. 37 (3), 185–199.

Gibbs, W.J., 1975. Drought, its definition, delineation, and effects. In Drought: Lectures Presented at the 26th Session of the WMO. Report No. 5. WMO, Geneva, pp. 3–30.

Estrela, M.J., Penarrocha, D., Milla´ n, M.,2000.Multi-annual drought episodes in the Mediterranean (Valencia region) from 1950–1996. a spatio-temporal analysis. Int. J. Climatol. 20, 1599–1618.

Dracup, J.A., Lee, K.S., Paulson, E.G., 1980. On the statistical characteristics of drought events. Water Resour. Res. 16 (2), 289–296.

Sen, Z., 1980.Statistical analysis of hydrologic critical droughts. J. Hydraulics Div., ASCE 106 (1), 99–115.

Zelenhasic, E., Salvai, A., 1987.A method of streamflow analysis. Water Resour. Res. 23, 156–168.

Frick, D.M., Bode, D., Salas, J.D., 1990.Effect of drought on urban water supplies. I: drought analysis. J. Hydrological Eng. 116, 733–753.

Clausen, B., Pearson, C.P., 1995.Regional frequency analysis of annual maximum streamflow drought. J. Hydrol. 173, 111–130.

Zecharias, Y.B., Brutsaert, W., 1988.The influence of basin morphology on groundwater outflow. Water Resour. Res. 24 (10), 1645–1650.

Vogel, R.M., Kroll, C.N., 1992.Regional geohydrologic–geomorphic relationships for the estimation of low-flow statistics. Water Resour. Res. 28 (9), 2451–2458.

Bravar, L., Kavvas, M.L., 1991.On the physics of drought. I. A conceptual framework. J. Hydrol. 129, 281–297.

Wheaton, E.E., 2000. Canadian prairie drought impacts and experiences. In: Wilhite, D. (Ed.), Drought: A Global Assessment, vol. I. Routledge Press, London, UK., pp. 312–330.

Wilhite, D.A., 2000. Drought: A Global Assessment, Vols. 1 and 2. Routledge, New York, 89-104, 1 and 2, Routledge, New York, pp. 129–448.

Wilhite, D.A., 2000b. Drought as a natural hazard: concepts and definitions. In: Wilhite, D.A. (Ed.), Drought: A Global Assessment, vol. 1. Routledge,

Bryant, E.A.,1991.Natural Hazards. Cambridge University Press, Cambridge. Byun, H.R., Wilhite, D.A., 1999.Objective quantification of drought severity and duration. J. Clim. 12, 2747–2756.

Panu, U.S., Sharma, T.C.,2002. Challenges in drought research: some perspectives and future directions. J. Hydrol. Sci. 47, 19–30.

Peters, A.J., Walter-Shea, E.A., Lei, J., Vina, A., Hayes, M., Svoboda, M.R., 2002.Drought monitoring with NDVI-based standardized vegetation index.Photogramm. Eng. Remote Sens. 68, 71–75.

APPENDIXES

Appendix1

Total monthly precipitation for basin for a year

```
Firstyear = dta[1,1]

ndata = nrow(dta)

Lastyear = dta[ndata,1]

monthlyprecip=c()

YYears =c()

MMonth=c()

monthlyPET=c()

for(year in Firstyear:Lastyear){

  log_indexY= (dta$V1 == year)

  # print(year)

  yearly_data = dta[log_indexY,]

  for(Mymonth in 1:12){

    log_indM = (yearly_data$V2 == Mymonth)

    mohlyvalues = yearly_data[log_indM,]

    monprec = sum(mohlyvalues$V4[mohlyvalues$V4>0])

    monthlyprecip=c(monthlyprecip,monprec)

    monPET=sum(mohlyvalues$V5[mohlyvalues$V5>0])

    monthlyPET=c(monthlyPET,monPET)
```

```
    YYears =c(YYears,year)

    MMonth = c(MMonth,Mymonth)

  }

}

plot(monthlyprecip,main ="scatter plots of Monthly precipitations from 1948-2003")

plot(monthlyPET)

monthlyprecip
```

Appendix 2

The calculation of Emperical probabilities

```
R=monthlyprecip

R

plot(R)

plot(R)

R

N=672

Rsorted=sort(R)

Rsortedcomplex=sort(R,index.return=TRUE)

Rsorted = Rsortedcomplex$x

IndsortedR = Rsortedcomplex$ix
```

```
myEcfd=c()
for(i in 1:length(Rsorted)){
  myEcfd[i] =   (i-0.35)/N
}
myEcfd
```

Appendix 3

Maximum likelihood estimation of parameter of Gamma distribution

```
R
mean(R)
log(mean(R))
W=log(mean(R))
W
K=sum(log(R))/N
K
A=W-K
A
alpha = 1/(4*A)*(1+sqrt(1+4*A/3))
alpha
beta = mean(R)/alpha
beta
```

Appendix 4

Calculate theoretical probabilities from Gamma distribution for each R[i]

```
myTcfd=c()

for(i in 1:length(Rsorted)){

  myTcfd[i] = pgamma(Rsorted[i], shape=alpha, scale = beta, log = FALSE)

}

MyTcfd
```

Appendix 5

Estimation of SPI index

```
sortdeSPI = qnorm(myTcfd, mean = 0, sd = 1)

SPI = sortdeSPI[IndsortedR]

plot(SPI,type="l",col='blue')
```

Appendix 6

Using spei package to calculate spi and spei for all the basins

```
library(SPEI)

SPI=spi(monthlyprecip,12)

plot(SPI)
```

Appendix 7

Estimation of SPEI

```
#SPEI=spei(monthlyprecip-monthlyPET,12)

plot(SPEI)

#Ways to eliminate the -inf values on the data, you shift the curve backwards.

y=monthlyprecip-monthlyPET

y

x=min(monthlyprecip-monthlyPET)

x

L=abs(x)

L

y+L

mydata=y+L

SPEI=spei(mydata,12)

plot(SPEI)
```