Spatio-temporal variability of change points at the scale of the Congo watershed using the Bayessian approach

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November 23, 2022

Abstract

The Lee and Heghinian's bayesian approach was applied to CRU TS 3.1 grid precipitation data to detect change points at the Congo watershed scale. The locations that were sensitive to change point have been widely detected during 1969 and have been grouped in two zones that are located mainly in (a) the sub-basins of Bangui and (b) the Kasai and in the Cuvette Centrale. The signal of the persistence over two zones has been estimated at 8 years and 15 years covering respectively the period 1966-1973 (78% of the years on the total area) and 19661-1975 (68% of the years on the total area). Moreover, the change points over mentioned zones are respectively associated with 85% and 77% of the negative values of the shift magnitude. However, about 20.0% and 10.6% of the total area of the Congo watershed were sensitive to change points and the base of precipitation, respectively.

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Key Points:

- Highlighting of the occurrence and persistence of two sensitive zones at the change points observed in the Congo watershed.
- Each of these two zones is characterized by a persistence of 8 (1966-1973) and 15 years (1961-1975).
- These two zones are located in the Bangui and Kasai sub-basins and in the Cuvette Centrale (inner plain or inner lowland).

Abstract

The Lee and Heghinian's bayesian approach was applied to CRU TS 3.1 grid precipitation data to detect change points at the Congo watershed scale. The locations that were sensitive to change point have been widely detected during 1969 and have been grouped in two zones that are located mainly in (a) the sub-basins of Bangui and (b) the Kasai and in the Cuvette Centrale. The signal of the persistence over two zones has been estimated at 8 years and 15 years covering respectively the period 1966-1973 (78% of the years on the total area) and 19661-1975 (68% of the years on the total area). Moreover, the change points over mentioned zones are respectively associated with 85% and 77% of the negative values of the shift magnitude. However, about 20.0% and 10.6% of the total area of the Congo watershed were sensitive to change points and the base of precipitation, respectively.

Key words: Spatio-temporal variability, Precipitations, Change point, Bayesian approach, Congo watershed.

1. Introduction

Change point can be understand as an abrupt change in the parameters of the distribution of a data set that occurs at a point where the data splits into two subsets with different statistical properties, such as mean, median, variance and interquartile range (Ryberg et al., 2019). It is important to note that the detection of a changepoint can be considered as evidence of a natural or anthropogenic change in climatic, hydrological or landscape processes (Ryberg et al., 2019, Perreault et al., 2000) and can help to quantify the excess or deficit (drought) of precipitation during a given period over a given region.

During 1970s and 1980s the African continent, particularly the north and west Africa has experienced a significant hydrological deficit (Mahé et Olivry., 1995, Bricquet et al., 1997, Houndenou et Hernandez., 1998, Morel., 1998, Servat et al., 1998, Laraque et al., 2001, Nguimal et Orange., 2013, 2019) that has been characterized by a high frequency of low water level occurrence (Bricquet et al., 1997, Kisangala., 2009, Pandi et al., 2009). A memory effect on base flows that leads to the depletion of water resources has also been reported (Wesselink et al., 1996, Bricquet et al., 1997, Orange et al., 1997, Laraque et al., 1998,2001, Olivry et al., 1998, Nguimalet et Orange., 2013, 2019). Morel (1998) has analyzed occurrence of the drought and its progression over the West Africa, including the Sahelian and the Gulf of Guinea zones. He found that the start of the drought has a space-time gradient. In fact, the drought has progressed from the northeast to the southeast (Morel., 1998). Thus, the equatorial zone, including the Gulf of Guinea (Houndenou et Hernandez., 1998) and the Congo Basin (Demarée et al., 1998, Asani., 1999, 2000) has also been affected. The causes of this rainfall deficit are multiples. We can mention the anomalies (space-time variation) of the ITCZ position, especially the reduction of its northward migration over the Atlantic Ocean (Lamb.,1978, Citeau et al., 1989) and physical processes related to the atmospheric and oceanic modes of variability, including the Atlantic Multi-decadal Oscillation (AMO) (Shanahan et al., 2009) and La Nina events (Druyan., 2011). According to Nicholson et al (2018), the Western equatorial Africa (i.e., the North of Angola, the Congo-Brazzaville/Gabon and the Cameroon regions), which represents the western side of the

Congo Basin, describes two opposites precipitation trends since the three last decades of the 20th century. Trends in Cameroon region mimics those in Sahel and the dryness conditions prevail since 1968, year during which an abrupt change or discontinuity in precipitation series has been detected over this region. In contrast to the Cameroon region, the Congo/Gabon and Angola are characterized by an increase of precipitation since 1980.

According to Ndehendehe et al (2019), more than 40% of the area of the Congo watershed was affected by persistent droughts during 1901-1930, 1994-2006 respectively and has particularly become drier during the last decade 1994-2014. This can reflect either the natural or anthropogenic changes in the climate process in this basin. The latter has also experienced an impact of climate change which has led to a slight modification of its water cycle (Lienou et al., 2008, Ndehedehe et al., 2019, Sonwa et al., 2020).

In the same way, the Ubangui sub-basin in Bangui has experienced the effects of rainfall variability on these water resources both on the surface and underground (Orange et al., 1997) that were much more pronounced in the northern part of the sub-basin (Orange et al., 1997, Runge and Nguimalet., 2005). A downward trend in floods and low flows and an increase in the severity of the low flow has been also observed in this sub-basin by several authors such as Orange et al. (1997), Runge and Nguimalet (2005) and Nguimalet (2017). Even if a memory effect was observed in the groundwater of the sub-basin (Orange et al., 1997, Nguimalet., 2017) a sponge-like delay was also observed between precipitation and runoff (Orange et al., 1997, Laraque et al., 2001, Nguimalet., 2017). Although the runoff deficit was much greater than that of precipitation, the precipitation time-series show a discontinuity in 1968, three years before the runoff discontinuity (Orange et al. al., 1997, Laraque et al., 2001). The effects of this variability in precipitation appear to be linked to a purely natural dynamic (Nguimalet., 2017).

Many other sub basins of the Congo watershed have experienced the either the precipitation deficit or discontinuity in precipitation time-series. Thus, the Sangha sub-basin describes a greater rainfall variation at the seasonal scale than at the annual scale (Samba et al., 2011) and show a discontinuity in precipitation time-series during 1970 (Laraque et al., 2001, Laraque et al., 2020), but has no significant change in annual precipitation (Laraque et al., 2020). In the Kasai sub-basin, rainfall has decreased and reached the lowest amounts during 1970 (Laraque et al., 2001, Kisangala., 2009, Tshitenge et al., 2016, Laraque et al., 2020). The effect of this decrease in precipitation on river runoff was observed 10 years later (Tshitenge et al., 2016, Laraque et al., 2001, 2020). Finally, the Lualaba sub-basin shows high precipitation in the early 1960s and a decreasing trend in precipitation towards the 1980s (Laraque et al., 2020). However, the chronicles of runoff from the Lualaba river in Kisangani show discontinuities in 1960 and 1964 (Laraque et al., 2020).

Several studies on hydroclimatic variability in space and time over West Africa, the Congo Basin at the whole or over smaller sub-basins are based on a local approach, which consists of performing analyze of a variable on one or more gauging sites in a region. For example, Paturel et al (1997) use nearly 200 rainfall stations to map the points of change before 1965, between 1965 and 1975 and after 1975 in West and Central Africa. However, many other studies are based on a global approach. This consists in estimating and using the spatially averaged precipitation of a given region to detect the changepoint. Comparatively, the global approach leads to spatially less or not diversified results or solutions while the local approach allows obtaining a spatial structure of changepoints over studied area.

The Congo Basin is the most significant wet zone of Africa, which is covered by the biggest bloc of the tropical rainforest of the continent (O'Loughlin et al., 2019). This forest is the most important sink of carbon in the world and the most important biodiversity hotspot. Congo Basin is also an important hydrological region in the World that covers more than 4.1 million km2 and its drainage represents 40% of the continent's total discharge (Crowley et al., 2006). Understanding the space-time variation in precipitation over the Congo Basin is an important task. It will lead, for instance, to understand the variation of the balance between precipitation and runoff, the evapotranspiration that explain the recent decrease in the river flow. Unfortunately, less attention has been deserved on this issue over the entire Congo Basin given to a lack of precipitation gauge data. As noted by Shem et Dickinson (2006), despite the resources the basin has, it has not yet received sufficient attention particularly in the domains of climate and hydrological research. Therefore, it seems important to extend the study of changepoint over the whole basin given to its significant ecological importance in order to determine the spatial range of changepoints and the temporal occurrence of the Sensitive Zones at change points as well as their persistence. This study is based on the assumption that only one change of the non-stationary occurs on an annual precipitation series. Therefore, it is not addressing the issues related with (1) the causes of non-stationarity which may be of anthropogenic origin or modifications of measurement or protocol equipment, etc. or (2) the multiple changes of change points.

2. Review of the literature on Bayesian change point approaches

Several approaches have been developed and can be used to detect changepoint in time series (Mood., 1954, Lee and Heghinian., 1977, Pettitt., 1979, Perreault et al.,1999, Rasmussen., 2001, Seidou and Ouarda., 2007, Seidou et al., 2007, etc.). They can be grouped into two categories: parametric approaches and non-parametric approaches. For example, the approach of Pettitt (1979) which detects the changepoint in the median, the Mann-Whitney test for location shift (Ross., 2015) is the non-parametric approaches. In contrast, the approach of Lee and Heghinian (1977) is a parametric approach which detects the point of change in the mean.

Non-parametric approaches are widely applied in the hydro-climatic domain than parametric approaches because although the non-parametric approaches always have the independent and uniformly distributed assumption as do parametric approaches but however they do not assume a particular statistical distribution (Machiwal and Jha., 2006, Ryberg et al., 2019). The parametric approach assumes the assumption of Gaussian distribution in time-series and consider that the parameters of the model may change at unknow moment in time (Gichuhi et al. 2012). It works better with transformed data, logarithmically for example (Ryberg et al., 2019). However, sometimes difficulties occur in interpreting a change in parameters (Jarušková., 1997) and often do not give satisfactory results.

Lubes - Niel et al (1998) show that only 40% of the sample simulated by the Bayesian approach of Lee and Heghinian succeed in detecting the points of change unlike the other approaches which detect the points of change at about 90 % of the simulated sample. Ryberg et al (2019) show that of the eight approaches to detect points of change in location and scale applied to a sample peak flow simulated by Monte-Carlo Markov, only two non-parametric approaches that of Mood's (Mood., 1954) and Pettitt (1979) gave satisfactory results. The parametric approaches did not work well with or without approximation of normality, whereas non-parametric approaches that detect more than one point of change gave an unacceptable number of points of change. It should also be emphasized that the persistence of hydro-climatic phenomena obscures the hypothesis of the independence of certain parametric approaches (Machiwal and Jha., 2006). For example, Lubes - Niel et al (1998) show that approaches requiring independence of successive observations are not robust with respect to a trend in a time series.

Despite the disadvantages of parametric approaches compared to non-parametric approaches (Machiwal and Jha., 2006, Ryberg et al., 2019), they have been applied in several studies. Among them we can mention Lee and Heghinian (1977), Bruneau and Rassam (1983), Maftei et al (2012), Berti et al (2012), Thiemann et al (2001), Perreault et al (1999, 2000), Tapsoba et al (2004), Rasmussen (2001), Seidou and Ouarda (2007), Seidou et al (2007), Ahokpossi (2018) that have been based on Bayesian parametric approach. The Bayesian approach assumes the a priori existence of a changepoint somewhere in a time series and gives at each time step an a-posteriori probability of this change (Lee and Heghinian., 1977, Bruneau and Rassam, 1983). Lee and Heghinian (1977) use the Bayesian approach to determine the marginal and joint posterior distributions of the changepoint of central tendency and scale. The Lee and Heghinian’s method was than applied by several authors to detect changepoint, such as Maftei et al (2012) for the eastern part of Romania, Bruneau and Rassam (1983) that applied a Bayesian model to detect shifts in the mean of series and determined the impact of the impoundment and operation of four water reservoirs on the monthly series of discharges observed on the Sainte-Anne River in Canada. Berti et al (2012) propose a Bayesian approach to determine the probability threshold on rainfall conditions likely to trigger landslides in Italy. Perreault et al (1999) present an extension of the Lee and Heghinian approach by introducing the possibility that no change in non-stationarity occurs in a time series using a detection procedure. The authors consider much more general earlier distributions that allow more flexibility in Lee and Heghinian's approach. The extension of the Lee and Heghinian approach is applied to the precipitation and discharge data series in eastern Canada and the United States during the 20th century. Finally, Thiemann et al (2001) propose a recursive Bayesian approach to reduce the uncertainty associated with the parameter estimates of hydrological models. They describe hydrological prediction in terms of the probabilities associated with different model output values (simple unit hydrograph model and Sacramento model). According to this study that the uncertainty associated with the parameter estimates is reduced recursively resulting from lower prediction uncertainties as the measurement data are successively simulated.

Tapsoba et al (2004) applied Bayesian approach proposed by Perreault et al (1999) on three precipitation grids corresponding to three selected areas in West Africa during the period 1950–1990. As results, they found that the most important rainfall changes in the Sahel most likely occurred between 1965 and 1970 with the decrease in the average level of rainfall. Rasmussen (2001) applied Bayesian approach to the generalized linear regression model and found that the combination of the linear regression model with the Bayesian approach is a practical framework for describing changepoints with a variety of associated changes.

More recently, Seidou and Ouarda (2007) proposed a Bayesian approach to detecting multiple change points based on multiple linear regressions. They found that the proposed approach is numerically efficient and does not take time for the simulation of the Monte-Carlo Markov chain. Ahokpossi (2018) applied the Seidou and Ouarda's approach (Seidou and Ouarda, 2007) to precipitation time series over Benin (West Africa) during 1940 - 2015. They conclude that changes in both central tendency and scale (variance) of precipitation time-series over Benin are not significant. However, most of the series exhibited changepoints corresponding to shift from humid to dry period (before 1968 and after 1990) and from dry to wet period (1969-1990). Seidou et al (2007) propose a practical and general Bayesian approach based on multivariate linear regression, which also takes into account missing data in the time series. The authors applied this approach to three examples to illustrate its characteristics and flexibility.

3 Study area

The Congo Basin is located in the heart of the African continent (Figure 1). It has an area of approximately 3665916.7 km^2 (Tshimanga, 2012) expanded from 09°20'N to 13°35'S and 12°05'E to 34°00'E. The Congo Basin is basically located in the Democratic Republic of Congo that accounts at least 63% of the total area. The rest of the area is distributed between

Cameroon (2.2%), CAR (10.9%), Angola (7.6%), Burundi (0.4%), Congo (6.7%), Tanzania (4.3%), Zambia (4.8%) and Rwanda (0.11%).

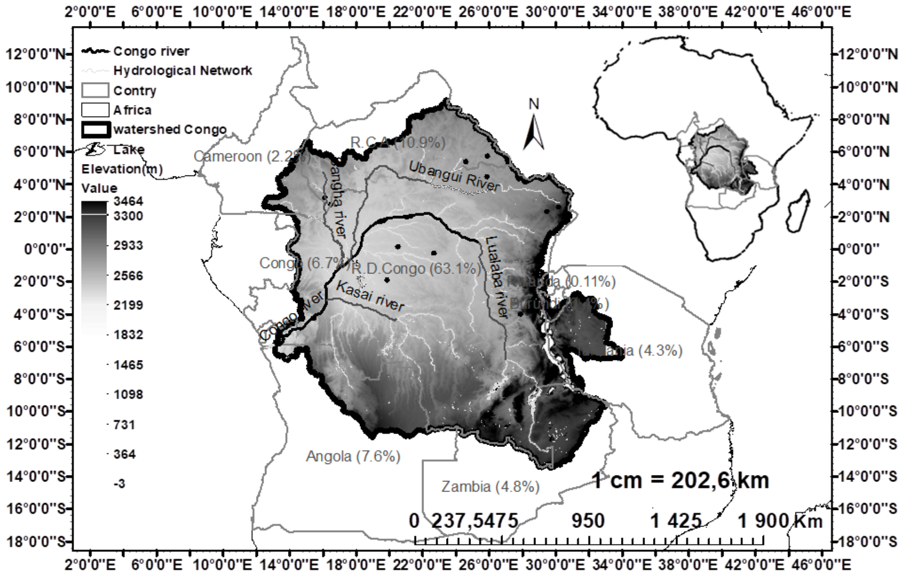

Figure 1 : Location of the Congo watershed in the African Continent. (D.R.C: Democratic Republic of Congo, C.A.R: Central African Republic, TZA Tanzania: United Republic of Tanzania).

The Congo River is the second in the world (Bricquet, 1993), both by its annual modulus estimated at 41000 m3 s-1 and by the size of its watershed (Bricquet, 1993; Laraque et Olivry, 1995). It is the only African river that has a dense hydrographic network. In addition, it is also characterized by its length: 4.700 km, and by a very low general slope of the order of 0.033% whose evolution from upstream to downstream is very irregular (Bricquet, 1993). The main navigable tributaries of the river are: Luapula, Lualaba, Lomami, Ruki-Tshuapa, Oubangi, Sangha and Kasai River. But the main tributaries that feed the river are: Kasai, Oubangi and Sangha (Bricquet, 1993). The position of the basin on both sides of the equator gives its river a very regular and stable bimodal hydrological regime (Bricquet, 1993).

A depression that does not exceed 400 meters of altitude dominates the center of the basin. It consists mainly of sandy sandstone formations and Mesozoic argillites topped with ferralitic soils. This depression is covered by a dense rainforest so that 35% of the basin area is partially flooded during floods (Laraque et Olivry, 1995).

The Congo Basin is subdivided into the following climatic zones: (1) the equatorial zone located on the center and astride the equator is characterized by an absence of a true dry season; (2) the tropical zone on the north and the south of equatorial zone; (3) the temperate zone over the mountains in the east (Bultot, 1971). In the equatorial zone of the Congo Basin the annual precipitation amount varies between 1500 and 2000 mm and the temperature average temperature is estimated at 26 ° C (Tshimanga, 2012).

However, its different characteristics give it enormous potential for the development of its water resources on a regional scale, such as hydropower, irrigation, navigation, etc.

4. Data

In this study, we used the CRU TS 3.1 gridded dataset provided by CRU (Climate Research Unit) of the University of East Anglia. The CRU uses an iterative homogenization procedure to obtain homogenized data. Based on this procedure, the reference series is used to correct any heterogeneity in the station records. The corrected data are then merged with the existing database and converted to anomalies (Mitchell et Jones 2005). The resulted anomalies were than interpolated to produce gridded data of 0.5x0.5 spatial resolution using the function Spline Technique and the Inverse Weighted Distance. Both techniques are adapted for data irregularly distributed in space. The CRU TS 3.1 dataset is described with details in Harris et al (2013).

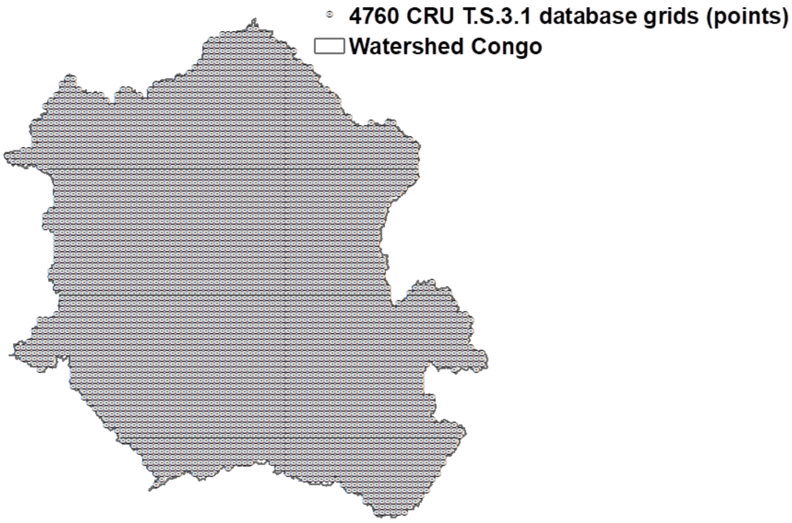

Figure 2 : The 4760 grids (points) of the CRU T.S.3.1 database which cover the entire Congo watershed.

The CRU climate data consist of concatenated global grids, in which the first line represents cells with centres on 89.75°S and the first column represents cells with centres on 179.75°W. Thus, the first cell in the file - and of every subsequent global grid is centered on (89.75°S, 179.75°W). For the purpose of this study, the CRU gridded data that cover the Congo Basin (with about 4760 grids) for the period 1940 to 2009 have been downloaded and then transformed to create monthly and annual time series. Thus, the dataset used in this study consists of the CRU T.S. 3.1 gridded monthly precipitation with spatial resolution of 0.5x0.5 for the period 1940-2009 and covering the entire area of the Congo Basin that accounts 4760 node points.

The CRU grid has already been proven globally and regionally (Döll et Fiedler, 2008; Tshimanga, 2012). In addition, this gridded dataset allows large scale studies and spatial analysis and is appropriate for large scale regions. Therefore, it may be more useful than a set of individual stations (Mitchell et Jones, 2005).

5. Methods

5.1 Choice of the Bayesian approach

The asymmetry, persistence and cyclicity of environmental data (Jarušková., 1997, Machiwal and Jha., 2006) give more flexibility to non-parametric approaches such as Péttit's approach than to parametric approaches such as Bayesian approaches. In fact, the assumptions of a particular statistical distribution are often the constraints for applying parametric approaches to environmental data unlike non-parametric approaches, which do not require these conditions. However, to overcome these constraints, approximations on environmental data are made (Helsel and Hirsch., 2002, Ryberg et al., 2019). Very often these approximations are logarithmic transformations (Ryberg et al., 2019). There are considerable number of approaches for changepoint detection in literature and therefore it is not easy to select the best one. Most authors offer simulations of a Monte-Carlo Markov sample and finally compare the different results of the approaches (Lubes - Niel et al., 1998, Ryberg et al., 2019). This comparison helps to decide on the choice of the best approach to use (Ryberg et al., 2019). For the purposes of this study, a changepoint approach to select should satisfy the at least the following conditions: first, the ability to associate to changepoints, the distribution of the a posteriori probability. Second, the single-shift models rather than multiple change points models. Third, the approach that involves an initial assumption of non-stationarity in time series. According to these reasons the Lee and Heghinian Bayesian parametric approach, which is a single shift model, has been used in this study.

The Lee and Heghinian approach, as described in Lee and Heghinian (1977), was applied on 4760 annual precipitation time series evenly distributed onto 0.5 x 0.5 spatial resolution grid over the whole Congo Basin. The logarithmic transformation was applied to the annual precipitation data in order to satisfy the assumption of normality required by parametric approaches.

5.2 Visualization of the occurrence of sensitive Zones at change points

The application of the Lee et Heghinian approach on 4760 time series of precipitations evenly distributed over the Congo Basin leads to a space-time representation of changepoints and these associated parameters. In fact, this approach results both in detection at various locations (spatial variation) of change point and these associated parameters, i.e., the date of change point (time variable), the posterior probability, magnitude of change as well as the unconditional posterior probability of the magnitude of shift (Lee et Heghinian., 1977, Bruneau et Rassam., 1983).

Evaluating the area covered by change points at the scale of the Congo watershed allows selection of the most dominant change point that covers the basin. This dominant point is then used to spatially represent the posteriori probabilities on the date of detection of this point. The analysis of the structure of this spatial representation allows us to visualize the occurrence of sensitive areas at the points of change on the date of the most dominant change point. However, the ratio expressed as a percentage of the area covered by a value of one of the change point parameters over the total area of a region is called an “area ratio” (Figure 3a) or “spatial range”.

5.3 Persistence of sensitive zones at change points

The persistence of a phenomenon can be defined as its similitude over time (Bunde et al., 2001) and is characterized by the temporal correlation (Ehsanzadeh and Adamowski., 2010). Several temporal correlations can be used in measuring the persistence, such as Pearson (1909), Spearman (1904) and Kendall (1948). The latter are the most widely used (Chok., 2008, Croux and Dehon., 2010, Mukaka, 2012). However, Pearson is a parametric approach unlike the other two which are non-parametric (Chok., 2008). The application of Pearson correlation requires normally distributed data and is sensitive to outliers (Chok., 2008, Joshi et al., 2021). Therefore, the transformation of data is used as solution before performing Pearson correlation (Box and Cox., 1964, Manly., 1976, Osborne., 2002) as well as the approaches involving the rank transformation (Spearman., 1904, Kendall., 1948). Croux and Dehon (2010) conclude that Kendall transformation has a slight advantage over Spearman because its distribution quickly converges to a normal distribution (Chok., 2008). Despite this slight advantage of Kendall's rank transformation over Spearman's, however, we preferred to use the spearman rank transformation to analyze persistence of the changepoint sensitive area.

In this study, the persistence of sensitive zones at change points is defined as residence times of values of the a posteriori probabilities over each one of the two delineated changepoint sensitive zones. It has been measured calculating the Spearman correlation coefficient between the change point posterior probabilities values of the reference year (which is 1969) over change point sensitive zone and the change points posterior probabilities values of the remaining years over the same change points sensitive zone. It expresses the persistence of temporal signal i.e., changepoint signal over the given geographical area.

6. Results and discussion

6.1 spatial range

Figure 3 below displays (a) the distribution of the spatial range of change points from 1943-2004, (b) the spatial ranges of posterior probabilities of change points, (c) the spatial range of the magnitudes of shift and (d) the spatial range of the unconditional posterior probabilities of magnitudes shift.

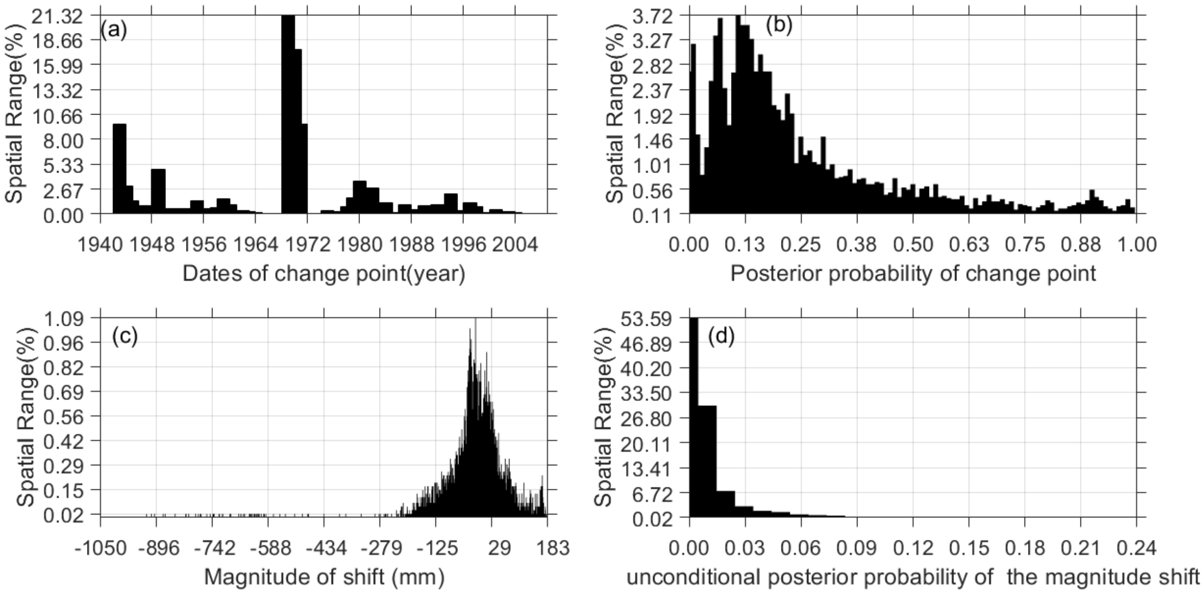

Figure 3: Spatial range of (a) dates of change points from 1943-2004, (b) posterior probabilities of change points, (c) magnitudes of shift and (d) unconditional posterior probabilities of magnitudes shift.

As it can be seen from Figure 3a, change points appeared and have been detected almost every year from 1943-2006 at least in one of the 4760 times series located somewhere in the Congo Basin. However, the mode of the distribution of spatial range appears in 1969 and decay in 1970-1972 which means that the signal of change point over the Congo Basin is strong in 1969. Therefore, 1969 year correspond to the year of change point in over the. This result is consistent with that found by Laraque et al (2001). They found a rainfall deficit of 4.5% during 1970-1980 compared to 1951-1969. Although changepoints have been detected in 1943 with the second important spatial range just after 1969 and 1970 (Figure 3a), unfortunately it is rejected due to the number of values used to estimate the change point (Ouarda et al., 1999). The spatial range in 1943 estimated at 10% (Figure 3a), is approximately equal to that of the year 1971. However, during 1968 the changepoint has no spatial range, i.e., it is very locally limited unlike 1970 whose spatial range is estimated at 18% (Figure 3a).

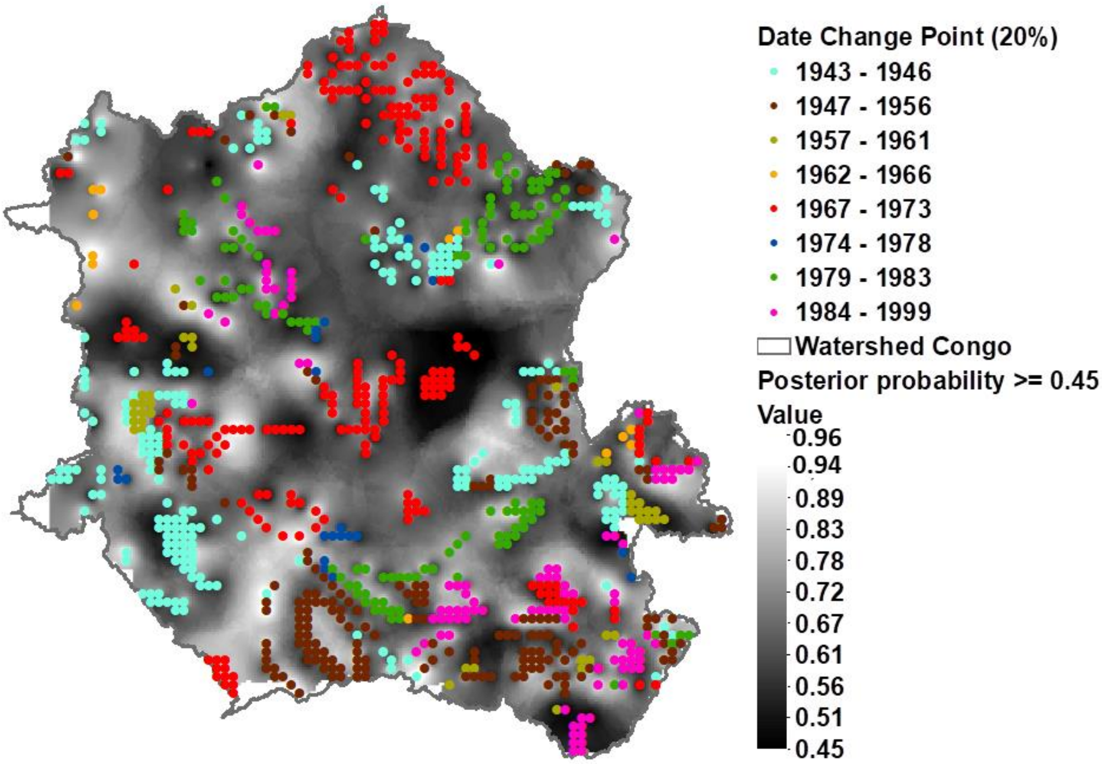

Figure 4: Values greater than or equal to 0.45 of posterior probabilities superimposed with periods chosen in an arbitrary manner of change points dates associated with those posterior probabilities values. The count of 992 grids (points) of change points associated with values greater than or equal to 0.45 of the a posteriori probabilities on a total of 4760 grids (points) which cover the entire Congo watershed shows that about 20% of the area basin was sensitive to change points.

Lee and Heghinia (1977) Bayesian approach estimates the posterior probability density function (hereafter referred to as the posterior probability of a change point), which associates the posterior probability on the point of change. The estimate of the spatial distribution of this function over the Congo Basin is presented in Figure 3b. Figure 3b shows that the posterior probabilities of change point varying between 0.00 to 0.27 have a very high spatial range at the basin scale. This spatial range reaches 66% of the total area of the basin. It should be noted that the value of 0.45 for the posteriori probability of change point represents the threshold from which the change point detection is acceptable. In other words, the posteriori probability values varying from 0.45 to 1.00 represent the confidence interval to detect the changepoint. This interval can also be referred to as the "changepoint sensitivity interval or simply the changepoint sensitivity". According to the figure 4, we estimate that about 20% of the area of the Congo Basin was affected by the change points.

Figure 3a shows the spatial range of change point over the Congo Basin and the Figure 3c the spatial range of their magnitudes. The figure 3c shows that the changepoint magnitudes vary between -209 mm and 183 mm over the whole (about 98% area) of the Congo watershed. The maximum value of 1.09% of spatial range is obtained at an offset magnitude of -15 mm (Figure 3c).

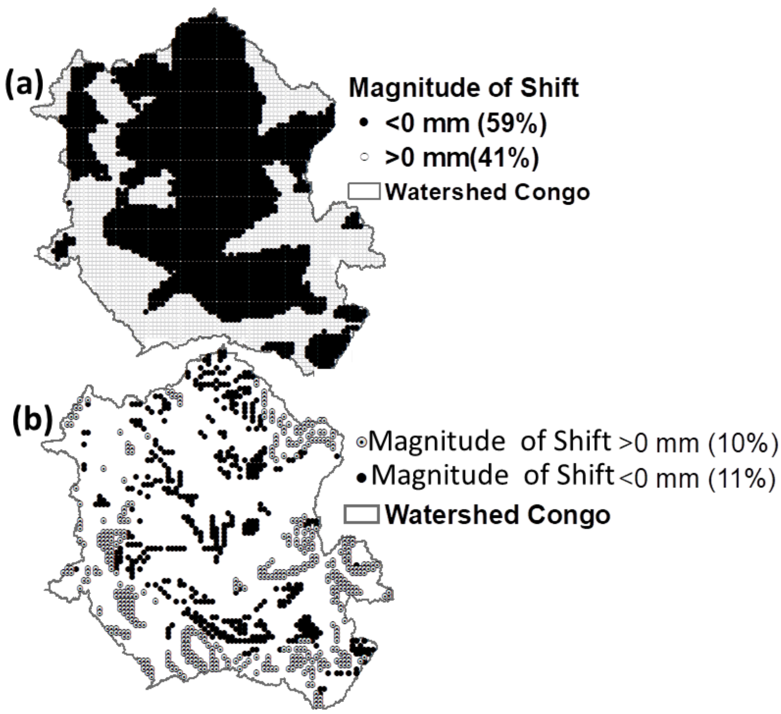

Figure 5: The negative and positive values of the shift magnitude to Congo watershed scale that cover: (a) 4760 grids (points) and (b) 992 grids (points) sensitive to change points. 59% of the points have negative shift magnitude values and only 11% are sensitive to decreased precipitation.

However, Figure 5 which presents the negative and positive values of the shift magnitude at the scale of the Congo watershed shows that about 59% of the area of the basin is occupied by negative values of the shift magnitude (figure 5a) and 11 % only are sensitive to the decrease in precipitation (figure 5b). These results show that rainfall across the Congo Basin decreased considerably during the study period (Figure 5). This agrees with previous results obtained by Laraque et al. 2001 on the scale of the Congo watershed. However, many other regions of the basin experienced increased precipitation (Figure 5). For example, in the west and east of the basin rainfall has increased unlike the northern, central, and southern parts of the basin (Figure 5).

Regarding the spatial range of the unconditional posterior probability of changepoint, it can be seen in Figure 3d that approximately 99.41% and 93.7% of the basin are affected by lower values varying from 0.09 and 0.03.

6.2 Delineation of changepoint sensitive zones

The spatial distribution of the different years during which the change points was detected highlighted the presence of homogeneous regions which deserve to be delimited. These regions can be taken as the sensitive zones to the change points occurred during 1969. Figure 6 below related to the posteriori probabilities of change during 1969 over the Congo Basin displays two homogeneous zones of change points. The first are, Zone 1, is located mainly in the Ubangui sub-basin in Bangui (Figure 6) with a tail southward in the Cuvette Centrale (inner plain or inner lowland) (Figure 6). The core of the second area, Zone 2, is located in the Cuvette Centrale, around Salonga National Park (figure 6) with two extensions that cover the Kasai-Basin. The first extension stretches out along the Kasai River and (2) the second extension cover the Kwilu and the Plateau of Batéké regions (figure 6). The Cuvette Centrale, particularly the region around Salonga National Park (Reinartz et al., 2006) that is the core of the second zone, is characterized by an intense healing during the year that leads this region being the one of the most important convection cells in the continent. It is also one of the rainiest areas over the Congo watershed. Thus, precipitation decrease over this region can leads to significant hydrological and ecological impact over the entire watershed.

Moreover, it can be seen in figure 6 that the posterior probabilities during the changepoint year 1969 are close to 0.00 over the whole Congo Basin, except for the two mentioned homogeneous areas (Figure 6). Some points in these two zones (Figure 6) have posterior probability values that reach 0.96.

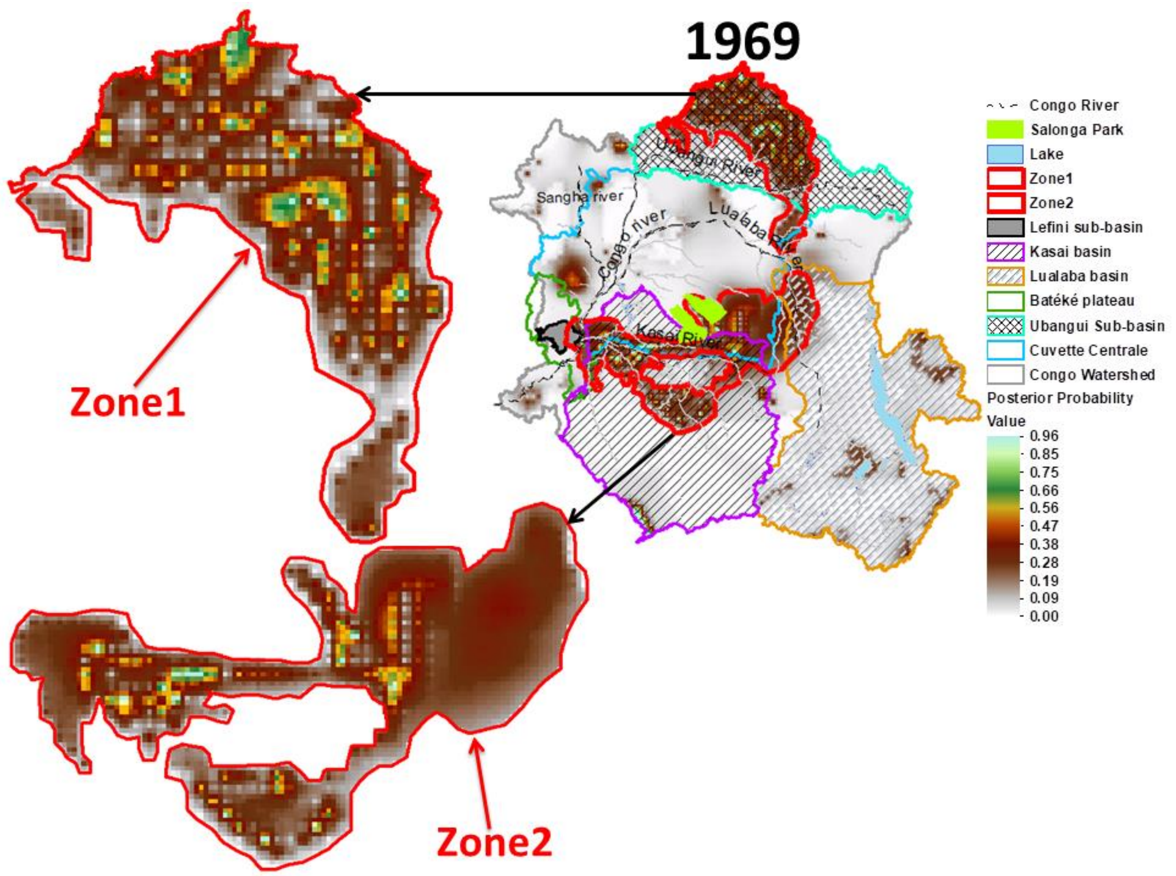

Figure 6: Superposition of the Batéké plateau, the central or Congolese basin, the main tributaries of the Congo rivers and as well as the sub-basins of Bangui, Kasaï, Lualaba with the temporal window of probabilities posterior to 1969. This superposition allows the geographical location of two sensitive zones at change points.

6.3 Persistence of the changepoint sensitive Zones

Figure 7 shows the spatio-temporal variability of two shapes of the posteriori probability structure delineated at 1969 over the period 1959-1978. It shows that the shape of the structure of the a posteriori probabilities on the two zones occurred several years before 1969, but in a lower proportion compared to the year 1969. From its first occurrence, the shape of the structure has weak spatial range of probabilities posteriori and little by little, its spatial range gradually increases over time, describing a spatio-temporal expansion up to itsmaximum at 1969, and then decreases from this year.

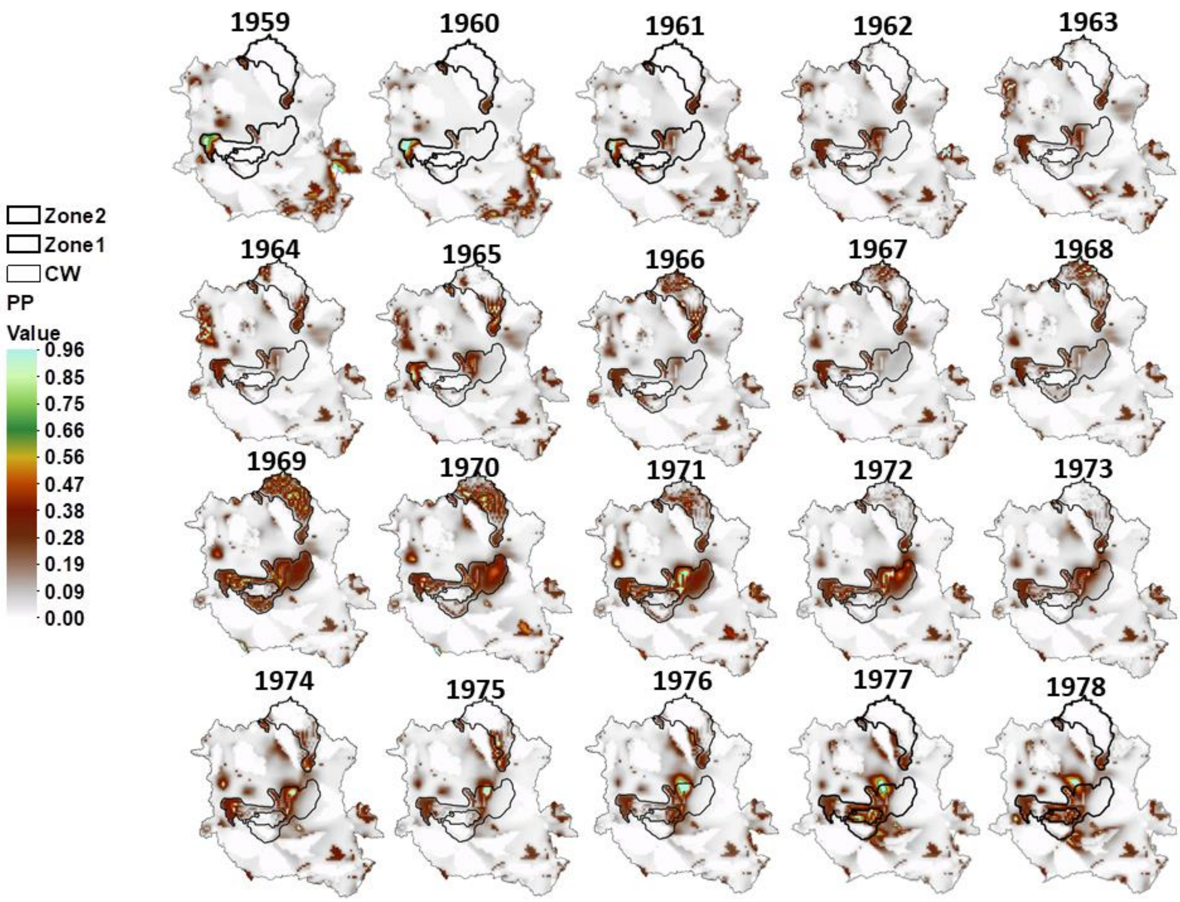

Figure 7: Spatio-temporal variation in the shape of the structure of the posteriori probabilities of zone1 and zone2 over the period 1959-1978. CW : Congo Watershed, PP : Posterior Probability.

Figure 8 presents: (a) the dates of change points, (b) the posteriori probabilities of these dates of change points and (c) the magnitudes of shifts associated with these dates on the scale of each of the zones on the period from 1943-2006. It shows that 78% of the total area of zone1 and 68% of the total area of zone2 are characterized by the years covering the period 1966-19973 and the period 1961-1975 respectively (figure 8a). In addition, 85% and 77% of the total area respectively of zone1 and zone2 are characterized by negative values of the magnitude of the shift, the maximum values of which reach -162.34 mm and -233.29 mm respectively (figure 8c).

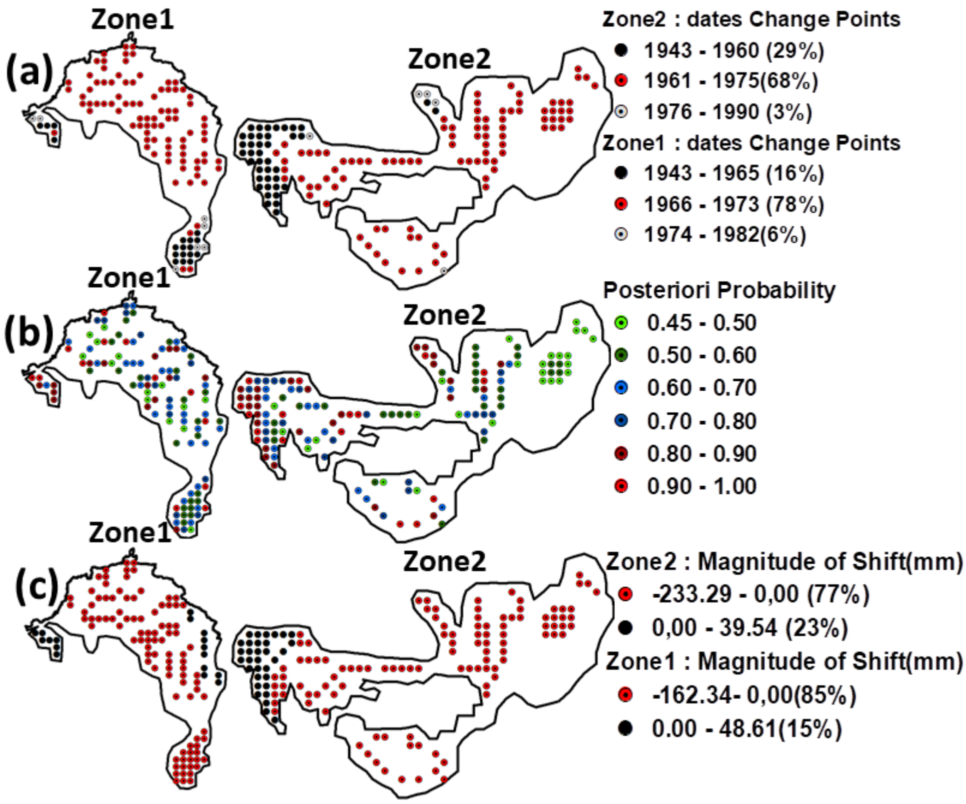

Figure 8: (a) the dates of change points, (b) the a posteriori probabilities of these dates of change points and (c) the magnitudes of shifts associated with these dates on the scale of each of zones over the period 1943-2004.

To select the year from which or to which persistence must be taken into account, a value of Spearman correlation coefficient (consisting of 0.44 or -0.44) from which the correlation is significant was used as threshold (Figure 9).

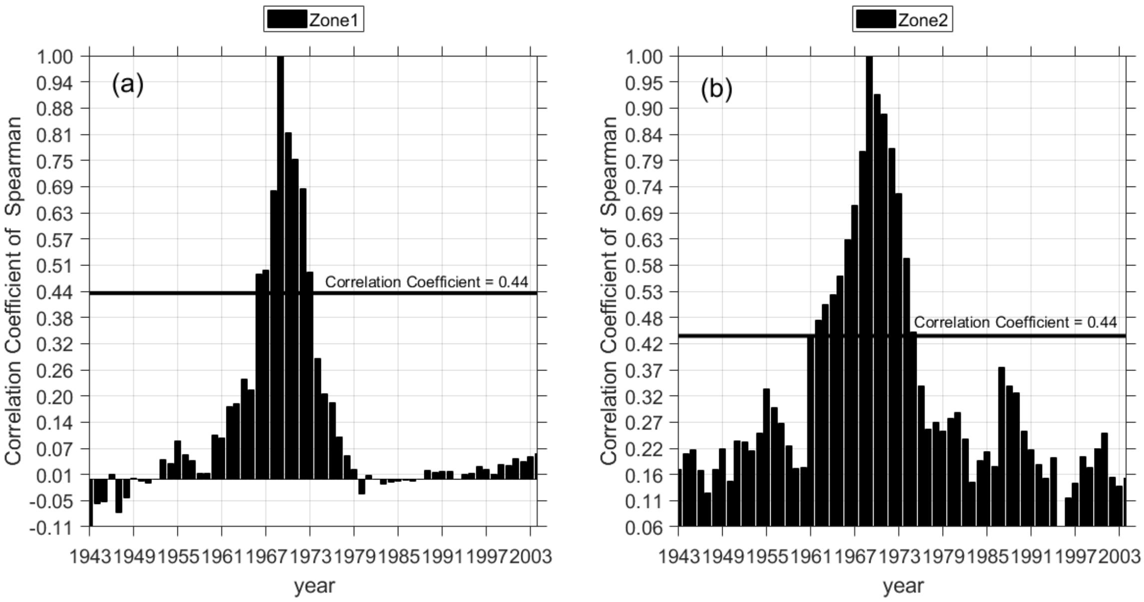

Figure 9: Spearman's rank correlation coefficient of the shape of the posterior probability structure of (a) zone1 or (b) zone2 of the time window at 1969 (taken as reference) on the same shape of the zone1 or zone2 to the time windows of posteriori probabilities covering the period of 1943-2004. The equation line Correlation coefficient = 0.44 shows the threshold set at the significant values of the correlation coefficients. The correlation coefficient value 1 shows that the year 1969 is taken as a reference for evaluating the coefficients of the Spearman rank correlations on the shape of the posterior probability structure of zone1 and zone2.

According to figure 9 and using the correlation threshold 0.44 (or -0.44), the strongest signal of posterior probabilities has spatially strong or persisted during 1966-1973 over zone1 and 1961-1975 over the zone2. In other words, zone1 persisted over a period of 8 years covering the years from 1966 to 1973. However, for zone2, the persistence lasted 15 years over a period covering the years from 1961-1975. Therefore, we can conclude that the effects of rainfall variability were much more persisted in the Kasai sub-basin than in that of the Bangui sub-basin.

Figure 9 also shows that the persistence of occurrence was not significant before 1966 in the zone1 and before 1961 in the zone2. Correlation coefficients were rejected because they were under the threshold significant value. In the same way, the persistence of occurrence was not significant after 1973 in the zone1 (figure 9a) and after 1975 in the zone2 (figure 9b). Although the correlation coefficient values are above the correlation threshold in 1975 (Figure 9b), the spatial structure of zone2 is distorted over this year (Figure 7). In other words, the spatial structure of zone2 tends to change in 1975 (figure 7).

The space-time variation of changepoint (figure 7) highlights the specificity of some geographical zones over the Congo Basin, where the space-time signal of changepoint was strong, that deserves to be pointed out. For example, the Ubangui Basin that is the core of the first zone, the Salonga Park that is the core of the second zone, as well as the Kasai Basin and Bateke Highlands. In the later mentioned geographical area no changepoints have never been detected before in previous studies (Laraque et al. 2001). The local-based changepoint detection performed in this study (figure 7 and figure 6) allowed bringing out abrupt changes in precipitation series over smaller geographical zones such as over the Bateke Highlands and the Lefini sub-basin. This could be explained not only by the smaller resolution of analyzed time-series but also the local particularity of some geographical zones that have an impact in analyzed runoff time-series. For example, the Lefini sub-basin has a powerful aquifer which plays the role in attenuating the flood peak, thus helping to minimize drought in the Batéké plateau (Laraque et al., 2001; Olivry, 1967) make this geographical being not sensitive to change points.

The Oubangui river in Bangui and the Kasaï river (Figure 1) experienced the problem of the decrease in the number of navigable days in the 1980s (Kisangala, 2009; Pandi et al., 2009). This problem therefore testifies to the extent of the persistence of sensitive areas at the points of change observed during the period 1961-1975 and which are characterized by a persistence of a rainfall deficit more than 75% (figure 8).

6 Conclusion

The merger of the local approach and the Bayesian approach of Lee and Heghinian apply on the CRU TS 3.1 precipitation database made it possible to detect a spatial distribution of change points at the scale of the Congo watershed. Changepoints have been widely detected during 1969 over major analyzed grid points grouped in two zones. Thoses two zones at have their cores respectively over the Ubangui sub-basin and around the Salonga Park. The sensitivity of the two zones to changepoints suggests that they are highly sensitive to precipitation variability. This fact deserves to be taken into account in the water management over these areas which, moreover, are drained by the two largest tributaries of the Congo River. The proportions of the area of negative values magnitude shift were estimated at 85% on the first zone and 77% on the second. This results in a decrease in precipitation in these two areas in particular on the Salonga National Park, which is one of the most important wetland and convection cells of the continent and could have negative impacts on the surface water flow over the basin. A further analysis that will address this issue should be useful.

The results found in this study are consistent to those found in previous studies. In fact, the changepoint in precipitation series during 1969 and the decrease in precipitation have been detected by several authors both at the scale of the Congo watershed and at the scales of sub-basins.

Moreover, the structure shape of the posterior probabilities of the two change point sensitive zones identified in the present study persisted during the period 1966-1973 (8 ans) for the zone 1 and the period 1961-1975 (15 ans) for the zone 2, respectively. This suggests that the effects of rainfall variability lasted much longer in the Kasai sub-basin than in the Bangui sub-basin. These effects were characterized by a decrease in precipitation estimate at around 20% of the total area of the Congo watershed. It should also be added that more than 65% and 75% of the proportion of the surface area of these zones is characterized respectively by the years of pointchange observed on the period 1961-1975 and by negative values of the magnitude of the shift. The remaining part of the basin seems to be affected very slightly by the change points and by its persistence over the 1961-1975 periods.

Although the spatial range was used to select time windows in this study, other available alternative, and effective methods can be used and would be helpful for this purpose. In the same way further studies can be carried out to understand oceanic and atmospheric events that can explain the variability of precipitation over to those two zones.

The point-based Bayesian approach seems to be an excellent tool for visualizing the occurrence and persistence of change point sensitive areas. However, even though it is not demonstrated in this paper, however, the results found using this approach are accurate in case of high quality and high-density rain gauge observations or high resolution grid precipitation data. In this context, a comparative study using for example the SIEREM grid (Environmental Information System on Water Resources - Hydrological Modeling) or other grids with the CRU grid will be very interesting. Likewise the results found in this paper are highly dependent on the method to be used. Indeed, it has been demonstrated that the percentage of detection of change points on a Monte-Carlo Markov sample is low using the Bayesian approach of Lee and Heghinian. In order, this study may well be extended to the scale of the African continent and to the planetary scale.

Acknowledgments

The precipitation data used in this study are available on the CEDA Archive website and can be downloaded via the link http://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_3.10/data. The four parameters of the Lee et Heghinian approach were estimated using a Matlab script. The different maps presented in this study use the ArcGIS script. However, extracting grid data CRU TS 3.10 in time series data uses a Python script. This work received no financial support. Authors are grateful to Dr. Marek Kaspar (from the Institut of Atmospheric Physics of The Czech Academy of Sciences) for remarks and considerations.

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