When every drop counts: Analysis of Droughts in Brazil for the 1901-2013 period

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Abstract

To provide information useful in policy formulation and management of drought impacts in Brazil, in this study, a sequence of drought events based on monthly rainfall of 1901-2013 on ~25 km x 25 km grid are derived at 4 timescales that include short-timescales (3-month and 6-month) and medium to long-timescales (12-month and 24-month). Subsequently, probability of drought occurrences, intensity, duration and areal-extent are calculated. The probabilities of occurrence of severe and extreme droughts at short-timescales are 1 in 12 and 1 in 66 years, respectively, all over the country. At medium to long-timescales, the probability of severe droughts is about 1 in 20 years in northern Brazil, and 1 in 10 years in the south. The probabilities of extreme droughts are 1 in 9 and 1 in 12 years over northern Brazil and in the south, respectively. In general, no evidence of significant ($\alpha = 0.05$) trend is detected in drought

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frequency, intensity, and duration over the last 11 decades (since 1901) at all the 4 timescales. The drought areal-extent show increasing trends of 3.4%/decade over Brazil for both 3-month and 6-month timescales. However, the trend increases for the 12-month and 24-month timescales are relatively smaller, i.e., 2.4%/decade and 0.5%/decade, respectively.

Keywords: Drought; risk management policies; Brazil; climate variability; living with drought; vulnerability

1. Introduction

As opposed to aridity that is restricted to regions of low rainfall, drought is a recurrent feature of climate variability that occurs in virtually all climate zones (Wilhite and Buchanan-Smith, 2005, Campos, 2015a), therefore, Brazil affords no sanctuary. In northeast Brazil, for example, whose impacts of severe droughts are well documented (e.g., Rohman 2013), devastating drought events trace back to the late 1500s (Lemos, 2003). As reported by Magalhães et al. (1988), the 1877-1879 droughts resulted in widespread famine that killed 4% of the population and displaced 3 million people. The 1979-1983 droughts on their part affected 18 million people, leading the government to spent about US$1.8 billion on emergency drought relief programs that consisted of distribution of food baskets, creation of emergency work fronts, and supply of portable water to communities (Lemos, 2003). Populations in other areas of Brazil are increasingly becoming aware of their vulnerability to drought due to water restrictions, power blackouts, and empty water reservoirs (Getirana, 2016). A good example is that of Cantareira water reservoir system, which provides water to approximately 8.8 million residents of Sao Paulo, Brazil's largest city. It registered less than 11% of its capacity in 2015 (VoA, 2016). This unprecedented drought may be a consequence of the depletion of moisture influx from the Amazon basin that normally brings rain to Central and Southeastern Brazil (Laurence and Vandecar, 2015). Rainfall pattern changes in the Amazon are attributed to the ongoing human-induced activities that include forest conversion and habitat degradation (Marengo et al., 2011, Nazareno and Laurance, 2015, Aragao and Malhi, 2007, Aragão et al., 2007). Nevertheless, generally vulnerability of a society to drought depends on many interacting factors, including population, social behaviour, policy, cultural composition, technology, land use patterns, water use, economic development and diversity of economic base (Naumann et al., 2013), even if drought levels remain unchanged.

Although the Inter-governmental Panel of Climate Change (IPCC) earlier reported that droughts have been worsening over some regions in recent decades while lessening in other parts of the world (Sheffield and Wood, 2008), the more recent special report (SREX), (IPCC, 2012) is more cautious, that there is no clear evidence of trends in the observed drought characteristics.

However, given that water resources are increasingly under pressure from rapidly growing demand associated with growing population and economic development, drought vulnerability to societies can remarkably be exacerbated (Vörösmarty et al., 2000). This is particularly true, if drought management policies remain unchecked.

Like many governments worldwide, Brazilian government has generally perceived drought as a natural risk to be mitigated through crisis management (i.e. by employing short term solutions). For example, the Brazilian government devoted itself to the construction of massive waterworks – reservoirs - and cloud seeding in the 1950s to 1990s programs but with little success (Lemos, 2003). It is evident that disaster-driven responses are not part of the learning needed to build resilience in socio-economic conditions (Wilhite et al., 2014). In addition, crisis solutions often favour poorer drought risk managers and climatologically marginal regions as recipients of drought relief assistance (Mpelasoka et al., 2008). Therefore, the increase in vulnerability of societies to droughts in many regions is a wakeup call for a more risk-based drought management strategy in the context of living with drought.

An overview of the risk-based concept and key principles of drought policy by Wilhite et al. (2014) provides a template (generic process) for the development of national drought policies. Technically, drought risk management requires adequate long-term statistics of the attributes of drought events (Kiem and Austin, 2013). For example, the quantification of drought frequency (or probability of occurrences), duration, intensity, and changes in areal-extent over time is not only essential in the policy making process, but also reinforces public accountability and democratization of informed decision making (Oliveira-Júnio et al., 2012, Teodoro et al., 2015b, Campos, 2015b, O.Saldan˜a-Zorrilla, 2008).

Although there has been a number of studies on drought in Brazil over the past decades (Teodoro et al., 2015a, Gois et al., 2013, Blain et al., 2010, Blain, 2012, Macedo et al., 2010, Li et al., 2008), hardly any study explicitly produced the desired statistics of attributes of drought characteristics for risk assessment. Most of them focused exclusively on the adequacy of drought indices and predictability of drought events. Nonetheless, there is still considerable disagreement about the concept of drought (Wilhite and Glant, 1985; Wilhite et al., 2014). It is our view that the disagreement is entrenched in the confusion emanating from lack of a clear distinction between drought and impacts of drought. For example, several indices including the popular Palmer Drought Severity Index (PDSI) (Palmer, 1965) and its derivatives, attempt to incorporate the interaction of land surface and other climatic variables (e.g. evaporative demand/near-surface temperature) on prolonged rainfall deficits. Apparently in that process, the concept of water or moisture accounting shifts the focus from drought assessment to impacts assessment. It is acknowledged that realistic drought impacts assessments are case specific endeavors, in terms of taking into account the diversity of different systems' aspects, e.g., the timescale of processes, system types (e.g., agricultural, hydrological and socio-economic) and anthropogenic effects (e.g., management and population). Therefore, the interpretation of such inclusive indices even if they can magically be made versatile remains a challenge. Consequently, the World Meteorological Organization (WMO) recommends all national meteorological and hydrological services to use the Standardized Precipitation Index (SPI) for monitoring of dry spells (WMO, 2012) towards consistent interpretation of drought phenomenon for practical purposes.

On the front of drought prediction, the teleconnection of climate variability El-Nino Southern Oscillation (ENSO) with rainfall anomalies has been extensively explored. However, in some areas of Brazil, for example, ENSO only explains a small fraction of the inter-annual variance of rainfall in the Amazon (Marengo et al., 1993). Similarly, Ropelewski and Halpert (1987) found that in almost all regions with coherent ENSO-related rainfall, time series of area-averaged seasonal rainfall departed by at least 80% of the ENSO events. Kane (1997) attributed the insufficient skill in both dynamic and empirical ENSO-rainfall models to the complexity of interactions among climate variability drivers.

To support the adoption of drought risk-management policy development in Brazil, the main objective of this study, therefore, is to estimate country-wide spatial distributions of (i) probability of occurrence of SPI-derived droughts in 3 categories (overall, severe, and extreme events), (ii) the 50^{th} and 90^{th} percentiles of drought intensity and duration, (iii) trends in duration, intensity, and areal-extent, (iv) association of 4 major large-scale climate variability drivers with rainfall anomalies; and (v) hydrological responses in relation to droughts at 3-month, 6-month, 12-month and 24-month timescales via runoff. Such statistical information is fundamental for the implementation of risk-management strategies for different timescales. In addition, such information on drought characteristics associated with the present-day climate variability, is required for performance evaluation of global climate models (GCMs). In order to have confidence in a GCM's drought projections, the first step is to demonstrate that the GCM-derived drought characteristics for the present climate, are convincingly similar to those derived from observations.

2. Data and Methodology

2.1 Data

Rainfall, runoff, and sea surface temperature (SST) are used in this study.

2.1.1 Rainfall and Runoff

Sets of time series of monthly rainfall (1901-2013) on a 0.5^{o} grid over Brazil were drawn from global datasets including the UK Climate Research Unit dataset (CRU)[2] (ts_3.22), GPCC (v7) from the Global Precipitation Climatology Centre (Schneider et al., 2011) and the Princeton Global Meteorological Forcing dataset (PRIN V2 for 1901-2012 (Sheffield et al., 2006)). Generally, these datasets exhibit similar patterns of correlation with the local Brazil dataset (1980-2013)[3], as depicted in Figures 1a through 1c, for the GPCC, CRU and PRIN, respectively. The median correlation values (for the grid-cells over Brazil) are 0.68, 0.67 and 0.67 for GPCC, CRU and PRIN, respectively. In addition, the Kolmogorov-Smirnov similarity (K-D statistic) test (Conover, 1971) at grid-cell level between local and global rainfall data, also show the same level of similarity for the GPCC and CRU datasets. As shown in Figure 1d through 1f, the K-D statistic provides the maximum difference between two cumulative distributions, while the p-value (Figure 1g through 1i) shows the probability of K-D statistic being equaled or exceeded. The median K-D/p-values for GPCC, CRU and PRIN are 0.08/0.15, 0.08/0.14, and 0.15/0.00,

[2] https://climatedataguide.ucar.edu/climate-data/cru-ts321-gridded-precipitation-and-other-meteorological-variables-1901#sthash.vZVTTM4N.dpuf
[3] https://utexas.app.box.com/Xavier-etal-IJOC-DATA

respectively. In this test, very small p-value (approaching zero) implies that the data samples are significantly different and vice versa.

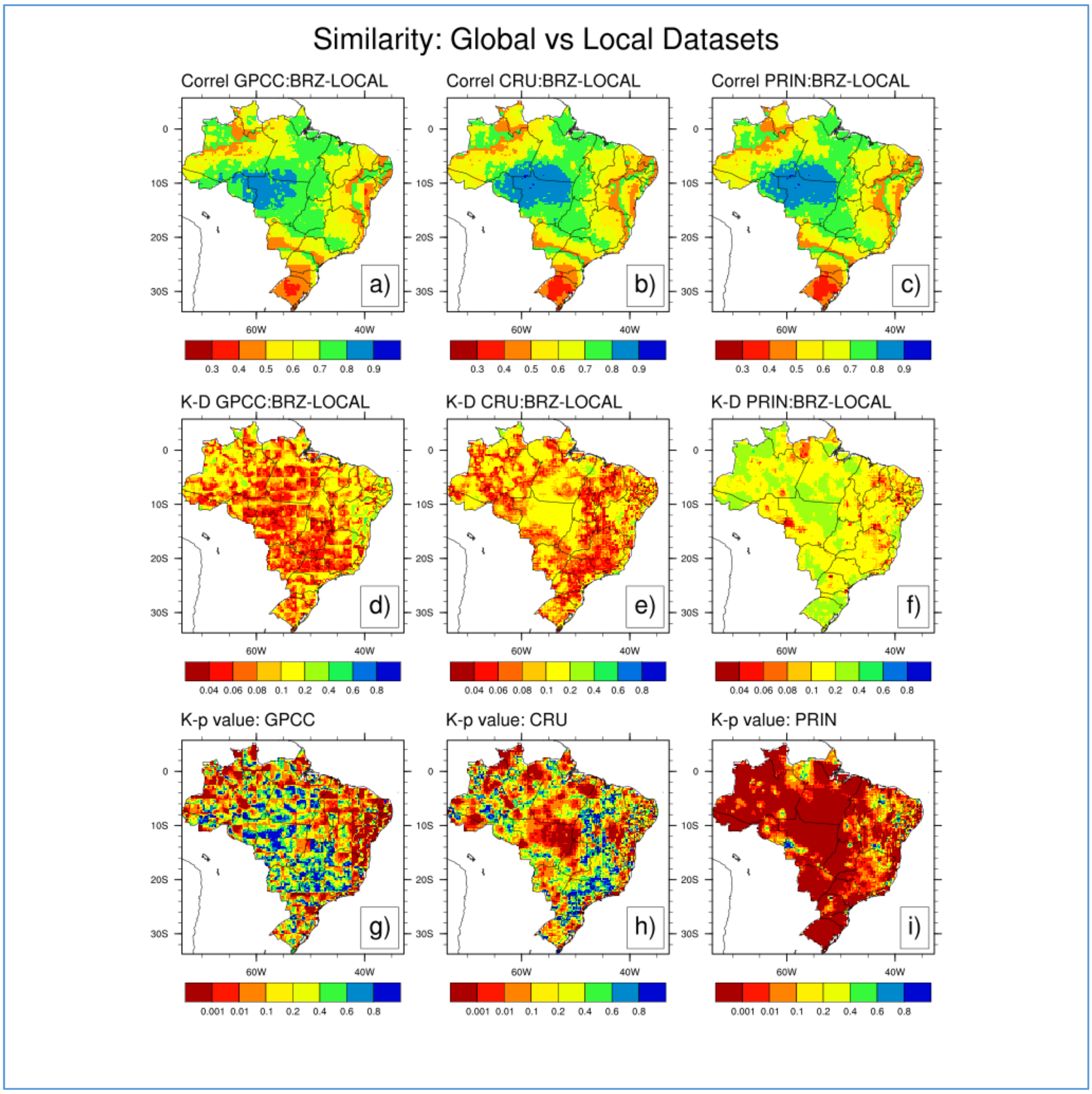

Figure 1: Correlation between Brazil local rainfall and (a) GPCC, (b) CRU and (c) PRIN datasets; Kolmogorov-Smirnov similarity statistic (K-D) between Brazil local rainfall and (d) GPCC, (c) CRU and (f) PRIN datasets and their respective p- values in panels (g) through (i).

A comparison of correlations between the three global datasets for 1901-1947, 1948-1999 and 2000-2013 periods is summarized in Table 1. The changes in the correlation between datasets over time would be a function of observation network on the ground. However, there is no evidence of remarkable improvement between the 1901-1947 period and the recent periods that are supposed to have better rainfall observation network. This demonstrates that there is skill in the reanalysis of the three global datasets that minimizes the influence of rainfall observation network on their products. Based on these findings, the CRU dataset was used in the subsequent analysis. However, due to the similarity demonstrated among these global datasets (i.e., Figure 1 and Table 1), any of these global datasets will give similar results as those obtained in this study.

Table 1: Correlation of monthly rainfall between the GPCC and CRU; GPCC and PRIN; and between CRU and PRIN datasets for 1901-1947, 1948-1999 and 2000-2013.

Period	Median monthly rainfall correlation value for grid-cells over Brazil		
	GPCC/CRU	GPCC/PRIN	CRU/PRIN
1901-1947	0.87	0.87	1.00
1948-1999	0.89	0.89	1.00
2000-2012/13	0.89	0.89	1.00

Monthly data (1950-2013) of gridded runoff were derived from daily modelled continental runoff on $\sim 0.25^{o}$ grid (http://stream.princeton.edu:9090/dods/GFDM/VIC_PGF/DAILY). This dataset is a product of a semi-distributed macro-scale Variable Infiltration Capacity (VIC) model (Liang et al., 1994) that simulates the land surface water balance. VIC accounts for modulation by vegetation of land-atmosphere moisture and energy fluxes, and attempts to represent sub-grid variability of vegetation, soil and terrain characteristics.

2.1.2 Sea surface temperature data

Sea surface temperatures (SST) datasets for the 1948-2008 period were drawn from the National Centers for Environmental Prediction (NCEP)-reanalysis (Kalnay et al., 1996). The SST data was used to calculate indices of the climate variability drivers that included the Oceanic Niño Index (ONI), the Indian Ocean Dipole (IOD), the Inter-decadal Pacific Oscillation (IPO) and the Tropical Atlantic Dipole Index (TADI). TADI has an impact of anomalously displacing the inter-tropical convergence zone (ITCZ) toward the north (south) leading to anomalous rainfall patterns and thus significant drying (wetting) over northeast Brazil (Cavalcanti, 2015).

2.2 Methodology

2.2.1 Standardized precipitation and runoff indices

Unlike continuous variables such as temperature, the representation of rainfall variability requires more complicated statistical calculations due to its episodic nature. The standardized precipitation index (SPI) is a probability index that gives a better representation of abnormal wetness and dryness. Mathematically, the SPI is based on the cumulative probability of a given rainfall event occurring at a location. The historic rainfall data of the location is fitted to a gamma distribution, since the gamma distribution has been found to fit the precipitation distribution quite well. The cumulative probability gamma function is subsequently transformed into a standard normal random variable with mean zero and standard deviation one (McKee et al., 1993). We adopt the concept of SPI in defining a standardized runoff index (SRI) as the unit standard deviation associated with the percentile of hydrological runoff accumulation over specific timescales.

2.2.2 Drought events

For this study, the SPI computing routine was applied to gridded monthly rainfall data to produce time series of monthly surfaces of SPI over Brazil at 3-month-, 6-month-, 12-month and 24-month timescales. For a given timescale, a drought event begins any time when the SPI is continuously less than negative 0.9 for at least 3 months, and ends when the SPI becomes greater than negative 0.9. This value is the threshold for dry conditions in the SPI classification, which is equivalent to 0.18 cumulative probability (McKee et al., 1993). By adopting the above definition, a simple systematic analysis of the SPI monthly time series (1901-2013) is carried out at each grid-cell to reveal drought events and their characteristic attributes of interest (i.e., frequency, intensity, and duration). Drought areal-extent, were determined by the grid-cells declared to be under drought on monthly basis across Brazil.

The differences in the structure of SPI time series of different timescales are illustrated in Figure 2. At short timescales (e.g., 3 months), SPI series at a grid-cell (e.g. 23.6°S, 46.6°W) exhibits high frequency of dry/wet spells of short duration (Figure 2a). As the timescale increases (Figure 2b through to d), the duration of spells gets longer and the frequency gets lower. The historical severe droughts of the 1920's, 1940's, 1953 and 1979-1983 (Lemos, 2003) are only evident in the SPI series of the 12-month and 24-month timescales, i.e., in Figure 2c and Figure 2d, respectively.

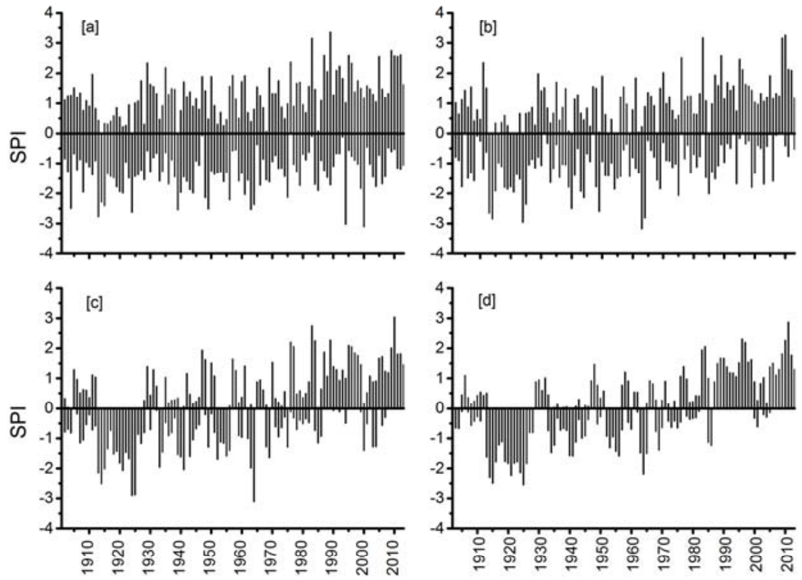

Figure 2: Illustration of differences in SPI time series structure at different timescales (a) 3-month, (b) 6-month, (c) 12-month, and (d) 24-month timescales at a grid-cell 23.6° S, 46.6° W in the neighbourhood of Sao Paulo.

Furthermore, spatially, the timescale concept enables the capture of changes in areal-extent of drought events. For example, the contrast between the drought areal-extent of the 1936 drought (Stillwell, 1992) in Figure 3 at different timescales is evident. At short-timescales of 3-month and 6-month, the figure exhibits a widespread drought (Figure 3a). At long-timescales of 12-month and 24-month in panels (c) and (d), however, the figure shows drought events of relatively small areal-extent. By accounting for the natural lags between accumulated rainfall deficit and systems' response, such as soil-moisture, river discharge, reservoir storages, and groundwater (Vicente-Serrano and L´opez-Moreno, 2005), the impacted system across the landscape can potentially be identified with confidence.

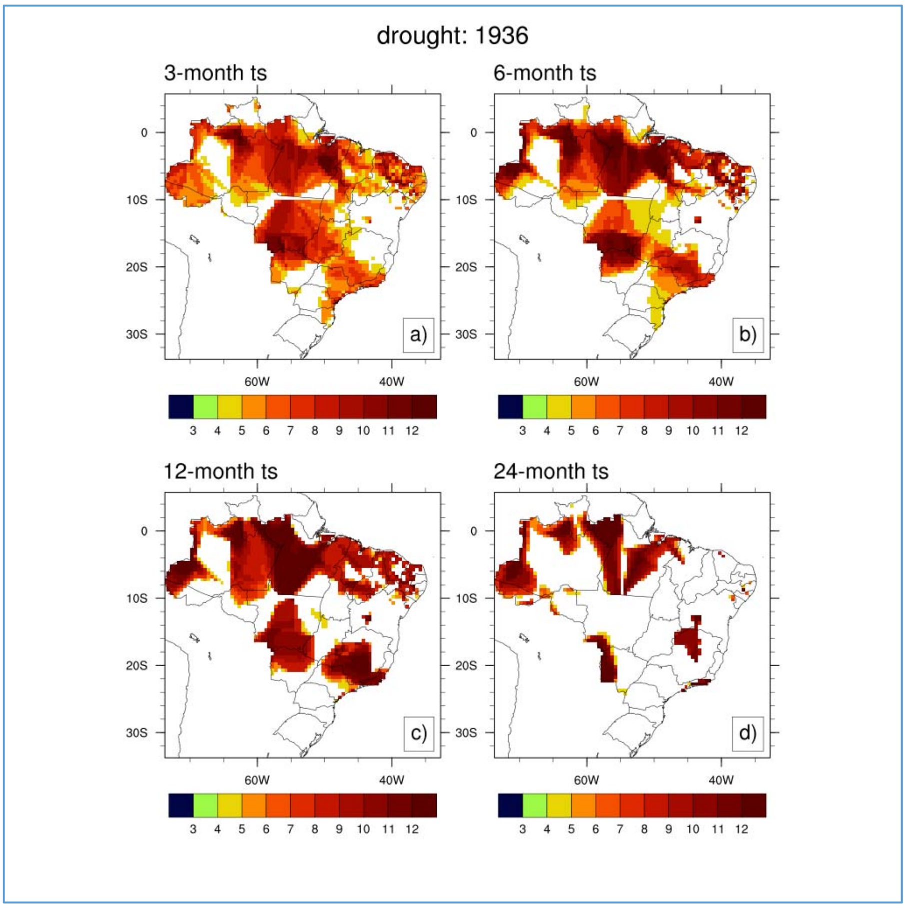

Figure 3: An illustration of the differences in drought duration (months) and areal coverage associated with timescales by the same drought event (e.g. 1936 drought): (a) 3-month, (b) 6-month (c) 12-month and (d) 24-month timescales.

The probability of a drought year was estimated by the relative frequency of the number of drought years to the total number of years for the 1903 April-2013 March. A year was set to run from April to March for the purpose of synchronizing with ENSO cycle, which is the dominant large-scale climate variability driver in the region. A drought event was deemed severe if it persisted for duration of 6 to 12 months, and was deemed extreme if the duration exceeded 12 months. The definition of the severity levels of drought can be arbitrary. Here we use drought persistence as a solely determinant factor of drought severity (i.e. level of impact), in that once the SPI-derived drought is declared, the system gets incapacitated, and therefore severity becomes a function of drought duration.

Subsequently, probabilities of severe and extreme (sometimes referred to as exceptional) cases were calculated as the ratio of the counts of the respective events to the total number of events. Finally, the probabilities of severe and extreme drought years were determined by multiplying the probability of drought years and the probability of severe, and that of extreme events, respectively.

2.2.3 Climate variability drivers

The ONI is an index of El Niño Southern Oscillation (ENSO) calculated as a running 3-month mean SST anomaly for the Niño 3.4 region (5^{o}N-5^{o}S, 120^{o}-170^{o}W). Events are defined as 5 consecutive overlapping 3-month periods at or above the +0.5^{o} anomaly for warm (El Niño) events and at or below the -0.5^{o} anomaly for cold (La Niña) events (Trenberth and Stepaniak, 2001).

The IOD is a natural ocean-atmosphere coupled mode that plays important roles in seasonal and inter-annual climate variations (Saji et al., 1999). It is the difference between SST anomalies in the western (50°E to 70°E and 10°S to 10°N) and eastern (90°E to 110°E and 10°S to 0°S) equatorial Indian Ocean. The index was calculated from the reanalysis SST data by the National Centers for Environmental Prediction (NCEP). The IPO index is the difference between the SST anomalies averaged over the central equatorial Pacific and the average of the SST anomalies in the Northwest and Southwest Pacific (Mantua et al., 1997). TADI is defined as the difference between the tropical North Atlantic (10°N–20°N; 20°W–50°W) and tropical South Atlantic (0°–10°S; 10°W–30°W) anomalous SST, and is related to an oscillatory coupled mode of the Atlantic multi-decadal Oscillation (Chang et al., 1997).

3. Results and discussion

Drought events were derived using SPI at 3-month, 6-month, 12-month and 24-month timescales on a 0.25°x0.25° grid over Brazil, for the 1901-2013 period. The subsequent analysis was focused on the long-term statistics of the attributes of drought characteristics and their spatial variations across the country. The hydrological response to rainfall anomaly at different timescales on simulated runoff on each grid-cell was examined for the 1950-2013 period. The spatial variation of the association of rainfall anomaly with four major large-scale climate variability drivers (ENSO, IOD, IPO, and TADI) that underpin drought occurrences were also examined.

3.1 Drought characteristics

Although drought can occur anywhere, the characteristics of drought events often vary among events and more importantly from region to region. Intuitively, the spatial variations are driven by the uneven distribution of individual responses to the climate variability drivers (examined in Section 3.5) and their interactions. The derived series of drought events over a period of about

112 years (i.e. a sample size of 1344 months) provided credible estimates of the probability of drought occurrence and *norm* values of relevant localized attributes of drought characteristics. Such information is considered fundamental for the development of drought risk-management and planning in the context of "living with drought".

As droughts tend to constitute conditions of aridity, the key objective of drought policies is to distinguish drought conditions that are rare and so protracted that they are beyond the scope of normal risk management practices of a system (or society) and justify institutional or governmental intervention. For example, the "Exceptional Circumstances" definition by Australia's National Drought Policy, introduced in 1992, takes a more realistic view of the climate variability (Mpelasoka et al., 2008).

This concept emphasizes that moderately dry conditions resulting in water stress are normal occurrences, and should pose risks best covered by "routine coping" strategies built in individual systems (e.g. hydrological or agricultural systems). By contrast, some form of institutional risk management best deals with rare and more severe drought events. Therefore a need for scientific guided criteria in quantifying the extent and severity of drought risks for Brazil cannot be over emphasized.

3.1.1 Drought occurrences

For risk management programmes, knowing the probability of drought occurrence is of basic importance.

Furthermore, such drought information at administrative levels is vital for a better interpretation of climate variability and change (Rojas et al., 2011). Figure 4a shows that the probability of 3-month timescale droughts in Brazil ranges from 12 to 22%, with low values mainly over the central areas. However, Figure 4b shows much less probability of severe droughts of 1 to 5%, with the northern and parts of western Brazil featuring higher probability than elsewhere. Figure 4c shows that extreme droughts at 3-month timescale are extremely rare with probability range of 0.2 to 0.9%. Although the overall probability for the droughts at 6-month timescale has values between 20 to 30% (Figure 4d), the probability of severe droughts ranges between 4 and 16% (Figure 4e), with relatively low values mostly over the northwest. Similarly, the probability of extreme droughts (Figure 4f) ranges between 0.5 to 2.5%.

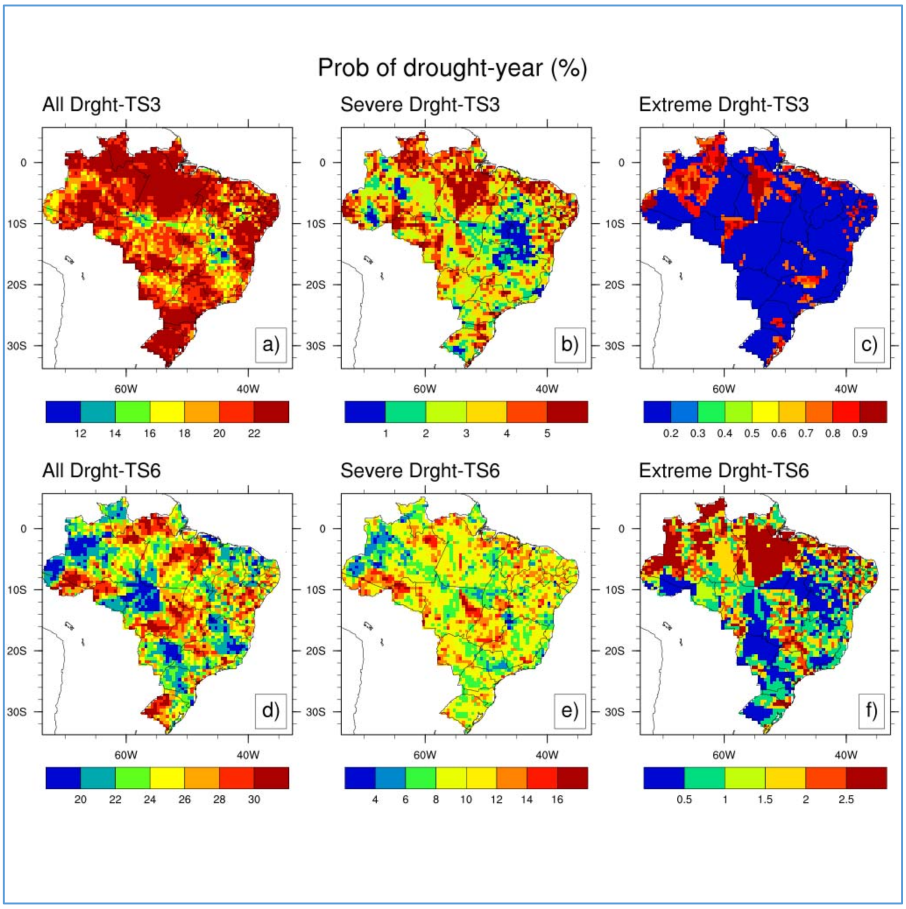

Figure 4: Probability (%) of a drought-year at 3-month timescale (TS3; (a) overall drought occurrence, (b) severe drought and (c) extreme drought) and at 6-month timescale (TS6; (d) overall drought occurrence (e) severe drought and (f) extreme drought).

Figure 5a shows the overall probability of droughts at 12-month timescale ranging between 19 and 27%, with lower values over the northern areas than those over the southern areas. The probability of severe droughts ranges from 6-10% and 10-14% for northern and southern Brazil, respectively (Figure 5b). On the contrary, the northern sector exhibited higher probability (7-11%) than the southern sector with average probability of about 5% (Figure 5c) for the extreme drought years. For the 24-month timescale droughts (Figure 5d), the overall probability for drought years is 16-20% over the northwestern and some parts of northeastern Brazil. The central and southern sectors show slightly higher probability for drought years of 21-24%. In 5e, the severe drought years over the northwestern show probability of 2-5%, and relatively higher elsewhere (6-10%). The probability of extreme drought years at 24-month timescale is 10-12% with higher values mainly over northern Brazil.

In summary, the probability of overall droughts at short timescales (e.g., 3-month and 6-month timescales) was estimated to be about 20% on the average (once in five years) across Brazil. However, the probability of severe and extreme droughts drops to about 8% (1 in 12 years) and 1.5% (1 in 66 years), respectively. More importantly, short-timescale droughts translate into agricultural droughts, and early stage of hydrological droughts that can only impact on river discharge in headwater areas (Vicente-Serrano and L´opez-Moreno, 2005, Patel et al., 2007). Therefore, only extreme droughts can impact reservoir storages and groundwater storage at short-timescales across Brazil.

On the contrary, for droughts at medium to long timescales (e.g., 12-month and 24-month timescales), regional differences in the probability of occurrences emerge. The probability for the overall and severe droughts, show relatively higher values (10%) over southern Brazil than elsewhere (5%). Consequently, it can be argued that droughts would devastate reservoir storages and groundwater storage more in southern Brazil than elsewhere. Surprisingly, the probability of extreme droughts on the average exhibited slightly higher values (11%) over northern Brazil than the southern sector (8%). Therefore for the same reasoning above, northern Brazil water resources are likely to be impacted only by extreme drought events.

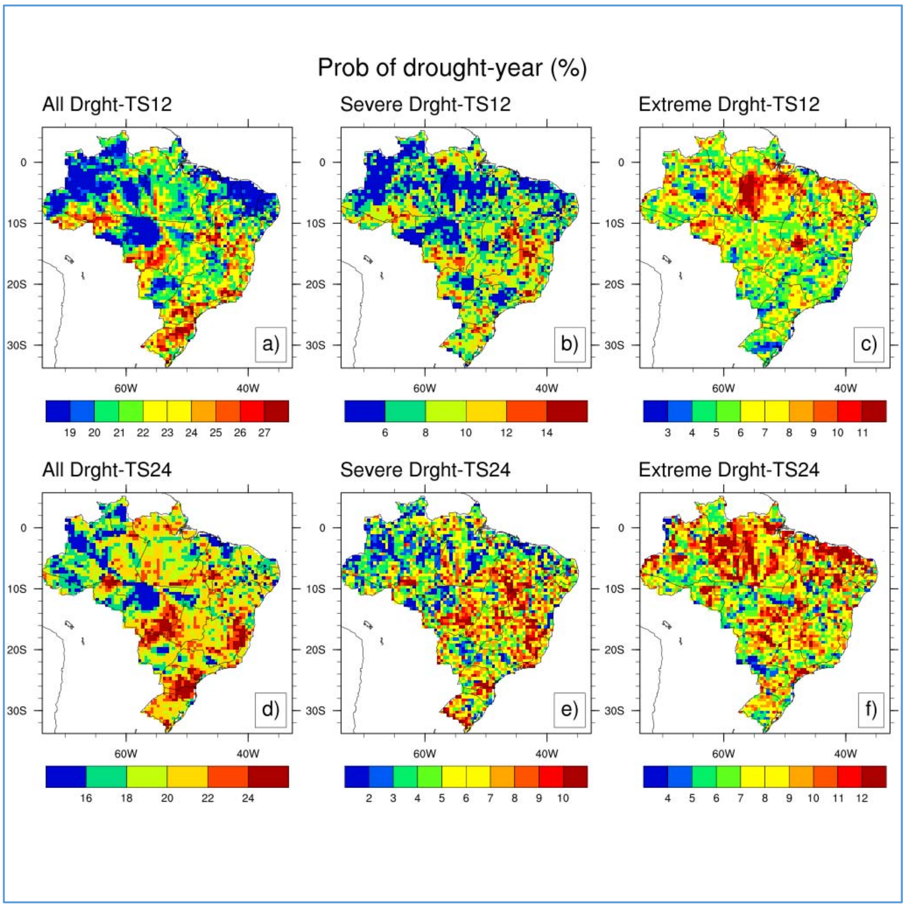

Figure 5: Probability (%) of a drought-year at 12-month timescale (TS12; (a) overall drought occurrence, (b) severe drought and (c) extreme drought) and at 24-month timescale (TS24; (d) overall drought occurrence (e) severe drought and (f) extreme drought).

Generally, drought frequencies show insignificant trends (α = 0.05) over the last 11 decades (Figure 6) at all the 4 timescales. However, a tendency of increases (0.01-0.2 events/decade) at all the 4 timescales is evident, except for the central areas of northern, northeastern and southern parts of Brazil, which show similar magnitudes of decreasing trends. The insignificant trend in frequency of historical droughts are consistent with other studies, for example, Worrall et al.(2006) and Sheffield et al.(2012) who showed that the previously reported increase in drought frequency (Briffa and G.& Jones, 2009, Wang et al., 2010) is an overestimate emanating from the use of Palmer Drought Severity Index. The demonstrated general insignificance of these trends is consistent with the more recent special report (SREX), that there is no clear evidence of trends in the observed drought characteristics (IPCC, 2012).

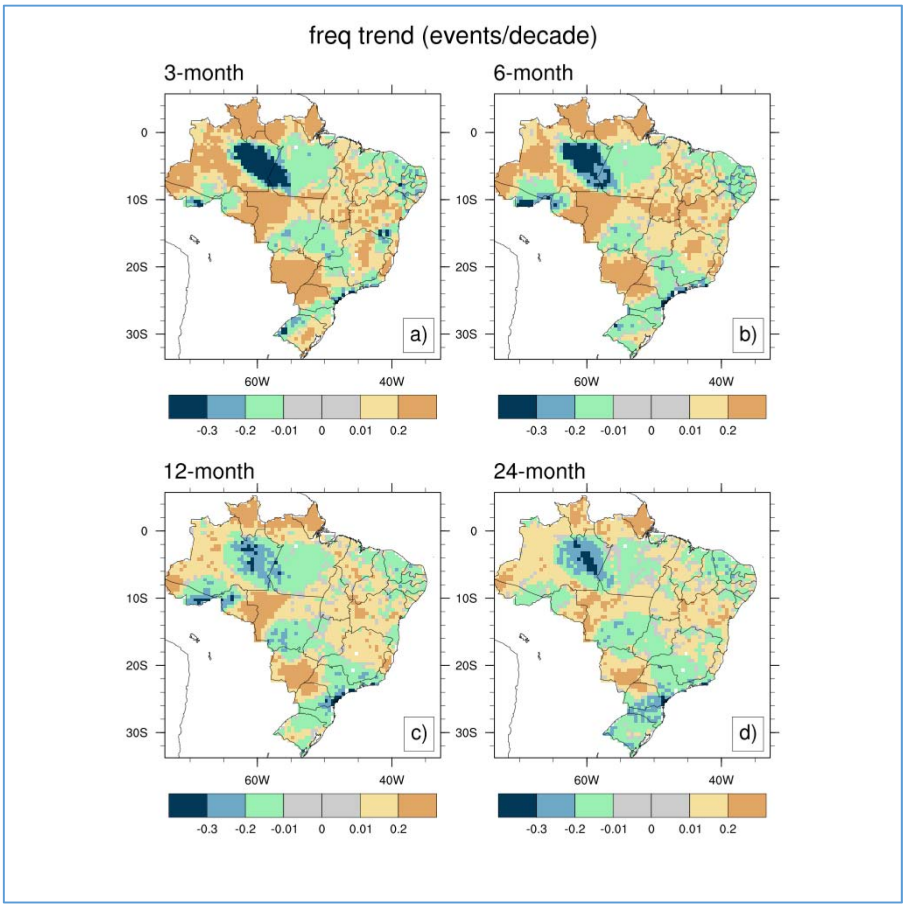

Figure 6: Trends in drought occurrence/frequency (months/decade) since 1901-2013 at (a) 3-month, (b) 6-month (c) 12-month and (d) 24-month timescales.

3.2.2 Drought intensity

Figures 7 and 8 show that except for the 24-month timescale, droughts of the 50th percentile intensity cause moderately dry conditions (i.e., -1.49 < SPI < -1.0) on the one hand. On the other hand, droughts of the 90th percentile intensity are associated with extreme dry conditions (SPI < -2) for most areas. The maximum (magnitude-wise) drought intensity in Figures 7c and 7f show that only the short-timescales (3-month and 6-month timescales) had intensity values in excess of -6.5 in some areas. The implication of excessively big drought intensity is the relatively slow rate of drought withdrawal, unless driven by unusual rainfall events.

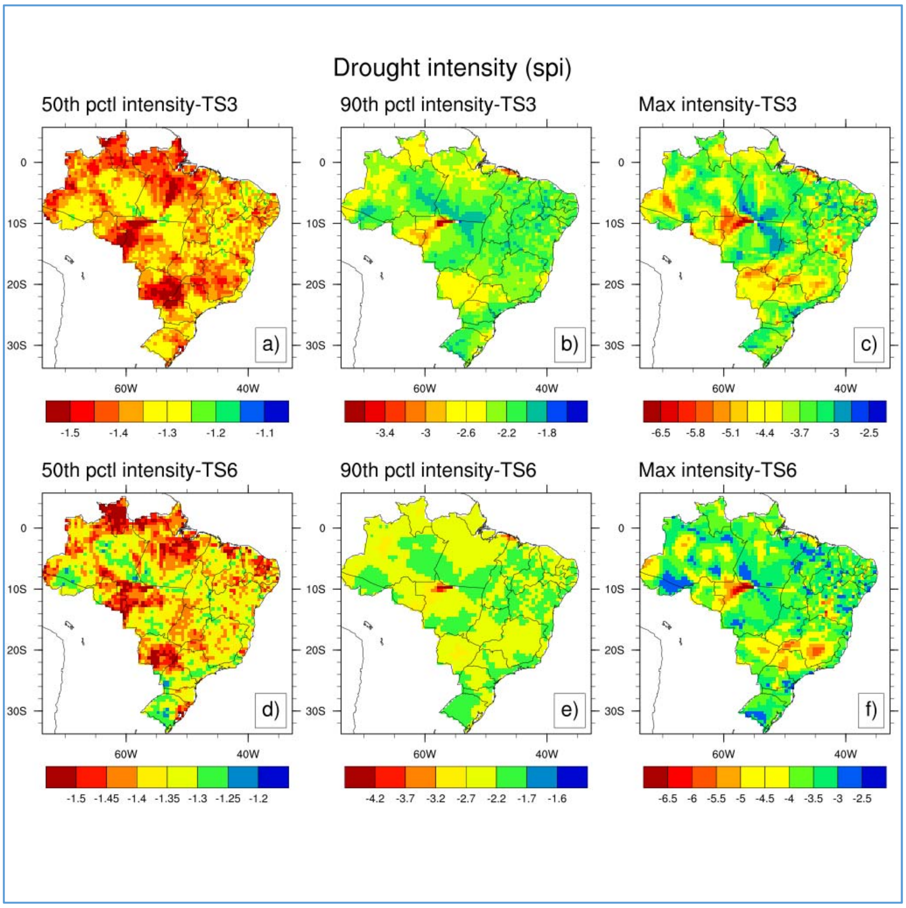

Figure 7: Drought intensity (SPIs) at 3-month timescale (TS3; (a) 50th percentile values, (b) 90th percentile values and (c) maximum values on record) and at 6-month timescale (TS6; (d) 50th percentile values, (e) 90th percentile values and (f) maximum values on record).

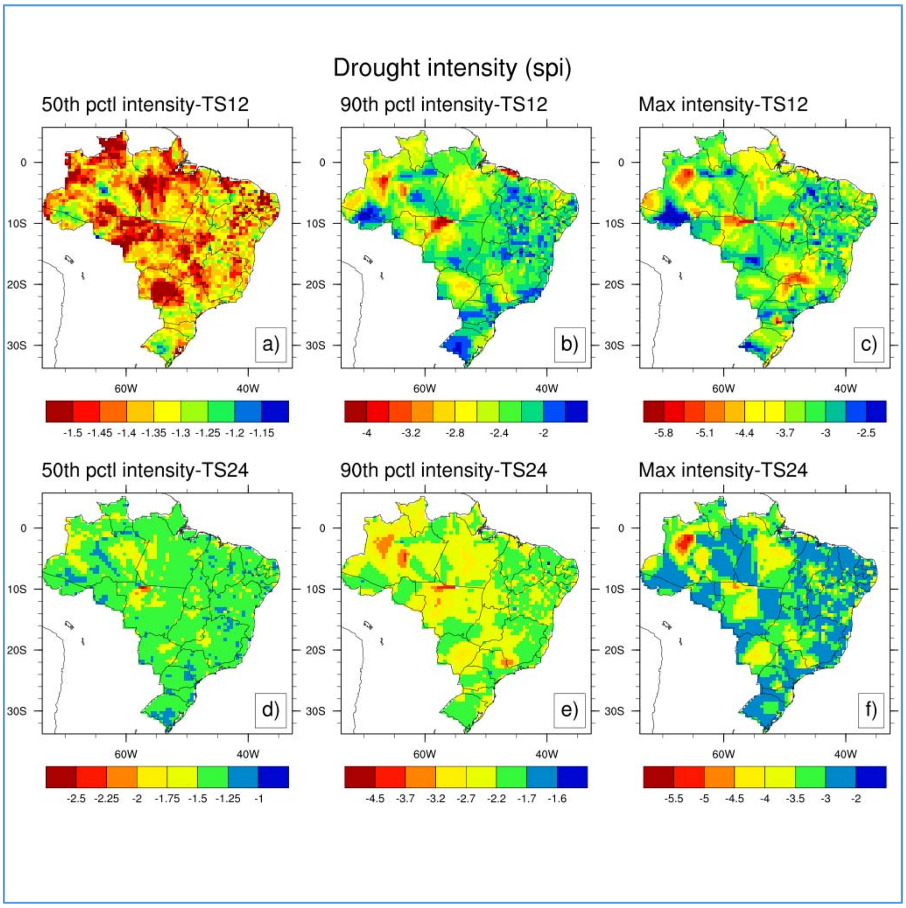

Figure 8: Drought intensity (SPIs) at 12-month timescale (TS12; (a) 50th percentile values, (b) 90th percentile values and (c) maximum values on record) and at 24-month timescale (TS24; (d) 50th percentile values, (e) 90th percentile values and (f) maximum values on record).

Figure 9 shows no significant trend (α=0.05) in drought intensity for all timescales, but a tendency of some reductions of up to -0.2 (SPI)/decade) for most areas, with isolated patches of increases of up to 0.1 (SPI)/decade over the Amazon and to the southern areas. It can be speculated that tendency of increase in intensity can be associated with the ongoing human-induced activities such as forest conversion and habitat degradation (Marengo et al., 2011, Nazareno and Laurance, 2015, Aragao and Malhi, 2007, Aragão et al., 2007) that tends to deplete moisture influx into the central and southeastern areas.

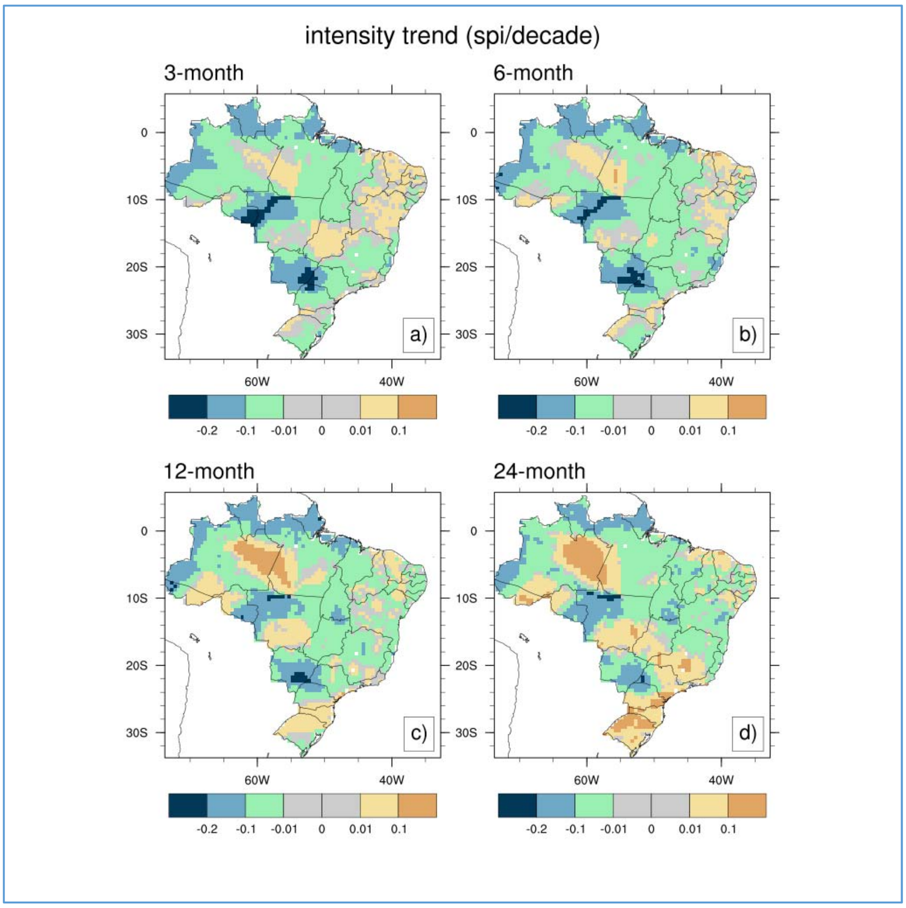

Figure 9: Trends in drought mean intensity (SPI /decade since 1901-2013 at (a) 3-month, (b) 6-month (c) 12-month and (d) 24-month timescales.

3.2.3 Drought duration

Over most areas, for the droughts at 3-month timescales, the 50th percentile values of duration are similar at about 4-5 months, except for the central areas with slightly shorter duration of about 3 months (Figure 10a). The 90th percentile values of duration range from 4 to 10 months (Figure 10b). High values of maximum duration (Figure 10c), which could be regarded as outliers are over the northwest (Amazon), up to over 40 months, while elsewhere the durations are from 5 to 20 months. Generally, drought duration tends to increase with increasing timescales for the 50th and 90th percentiles' values of drought duration, as depicted in Figures 10 and 11.

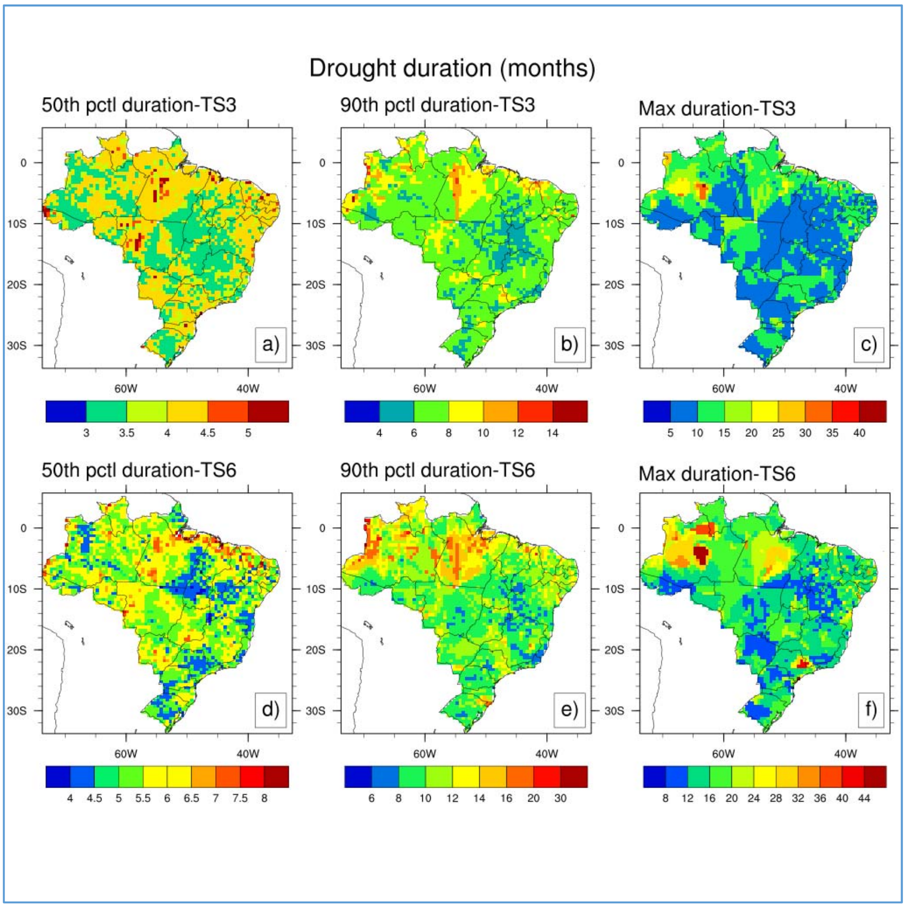

Figure 10: Drought duration (months) at 3-month timescale (TS3; (a) 50th percentile values, (b) 90th percentile values and (c) maximum values on record) and at 6-month timescale (TS6; (d) 50th percentile values, (e) 90th percentile values and (f) maximum values on record).

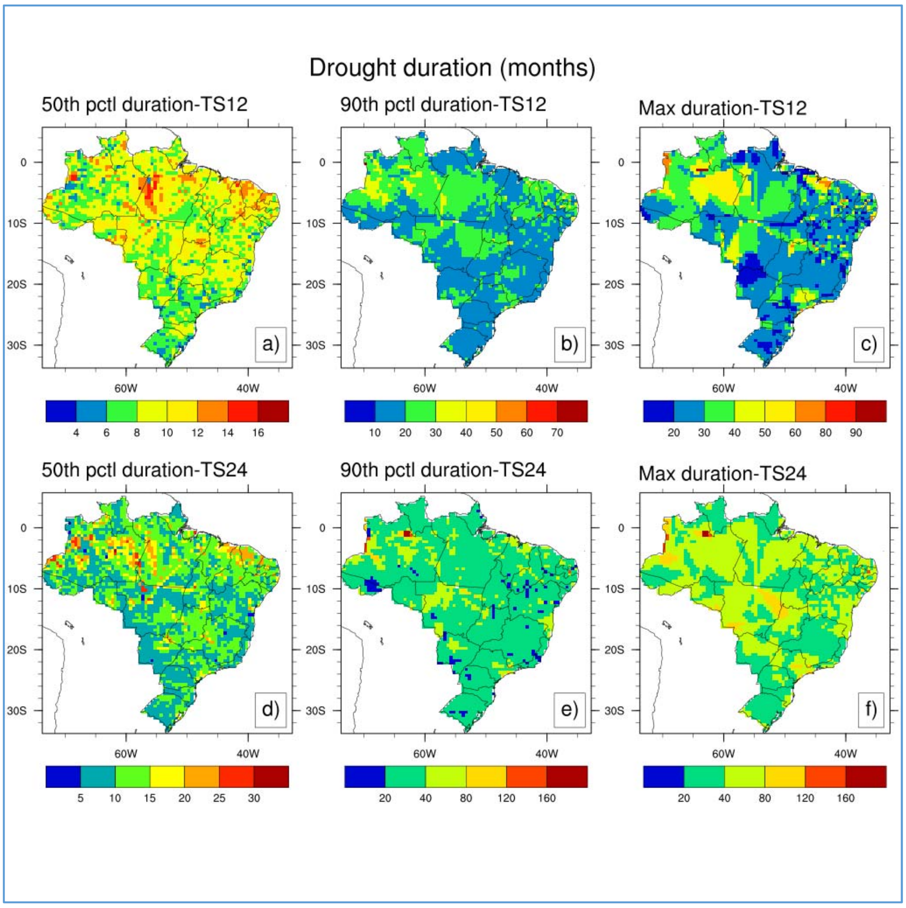

Figure 11: Drought duration (months) at 12-month timescale (TS12; (a) 50th percentile values, (b) 90th percentile values and (c) maximum values on record) and at 6-month timescale (TS24; (d) 50th percentile values, (e) 90th percentile values and (f) maximum values on record).

Figure 12 shows no significant trend in the drought duration as well, however, for the 12-month and 24-month timescales, the tendency of decreasing duration is dominant in the central areas of northern Brazil and to the south.

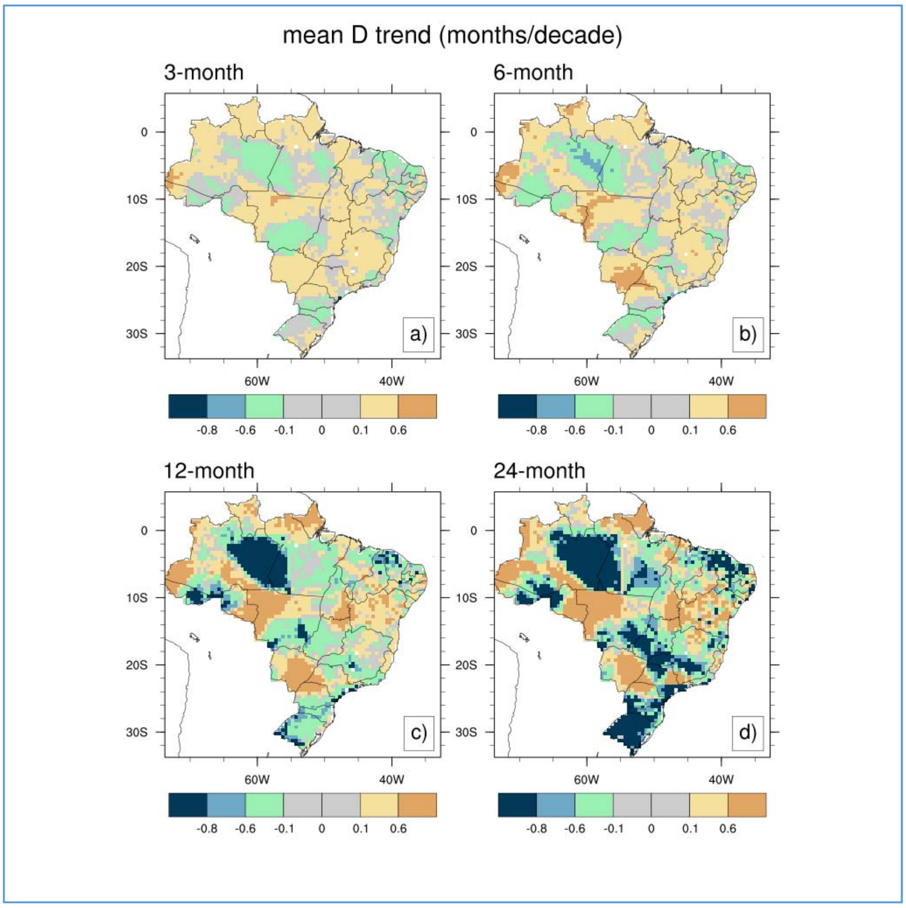

Figure 12: Trends in drought mean duration D (months/decade) since 1901-2014 at (a) 3-month, (b) 6-month (c) 12-month and (d) 24-month timescales.

Figure 13 shows increasing trends in drought area-extent of 2.8 x 10^{-4} proportion of Brazil land area/month (3.4%/decade) for both 3-month (panel a) and 6-month (panel b) timescales. The increasing trends for the 12-month (panel c) and 24-month (panel d) timescales are relatively smaller, i.e., 2.0x10^{-4} proportion of Brazil land area/month (2.4% /decade) and 4.0x10^{-5} proportion of Brazil land area/month (0.5%/decade), respectively. However, analysis based on relatively short periods can easily lead to different trend direction, for example, Sheffield et al., (2009) demonstrated a decreasing trend in the areal-extent for South America continent for the

1958-1997 period, by a list of drought areal-extent {9.0, 6.5, 6.3, 5.1, 5.0} x 10^6 km^2, corresponding to drought events of {1963/64, 1961, 1968, 1951, 1997-98} respectively. This data suggests a negative trend in areal-extent of about 0.0257x10^6 km^2/year over South America. This is consistent with the Brazil data as shown in Figure 13 for the 1958-1997 period, nevertheless, that trend does not account for the multi-decadal variability present in the long-term time series.

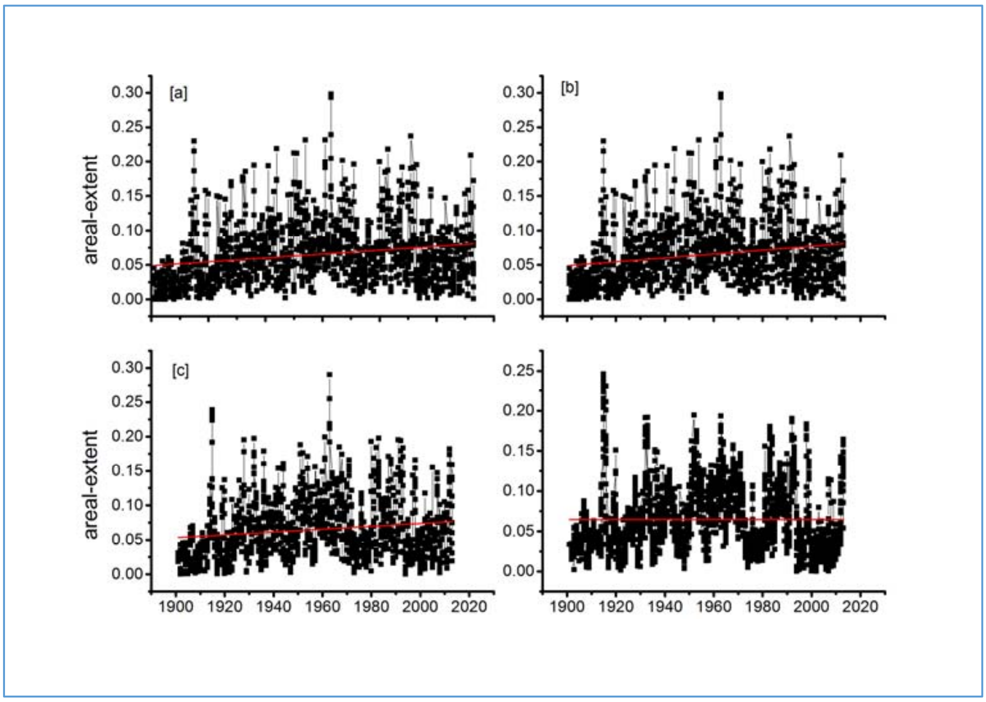

Figure 13: Trends in areal-extent of monthly SPI < -0.9 coverage across Brazil panel (a) 3-month, (b) 6-month, (c) 12-month, and (d) 24-month timescales.

3.4 Hydrological response to meteorological drought

In essence, drought is more precisely perceived in the context of rainfall deficit, and apparently the so called “agricultural” and “hydrological” droughts are just impacts of drought ("meteorological") on those systems. Indeed, the impacts of drought on agricultural and hydrological systems can be exacerbated by factors such as the atmospheric evaporative demand, the dynamics of land surface, and anthropogenic effects (e.g. management etc.). Therefore, realistic impacts of drought can explicitly be assessed through semi-distributed conceptual/physical models driven by relevant potential variables in addition to rainfall which, accounts for the drought effect (Wilhite et al., 2014).

The variation of hydrological response to rainfall anomalies over Brazil are illustrated by the differences in the correlation between rainfall anomalies (SPI) and runoff anomalies (SRI) for the 1950-2013 period (Figure 14) as shown in panels (a) through (d), for 3-month, 6-month, 12-month and 24-month timescales, respectively, the pattern of the correlation becomes prominent at long-timescales (12 and 24 months). This is because the indices integrate over the entire water-year, exceeding time for most effects of hydrological modulation (Shukla and Wood, 2008). Generally, the correlation between SPI and SRI is higher in areas with relatively high rainfall (northern, northwest, and southern sectors).

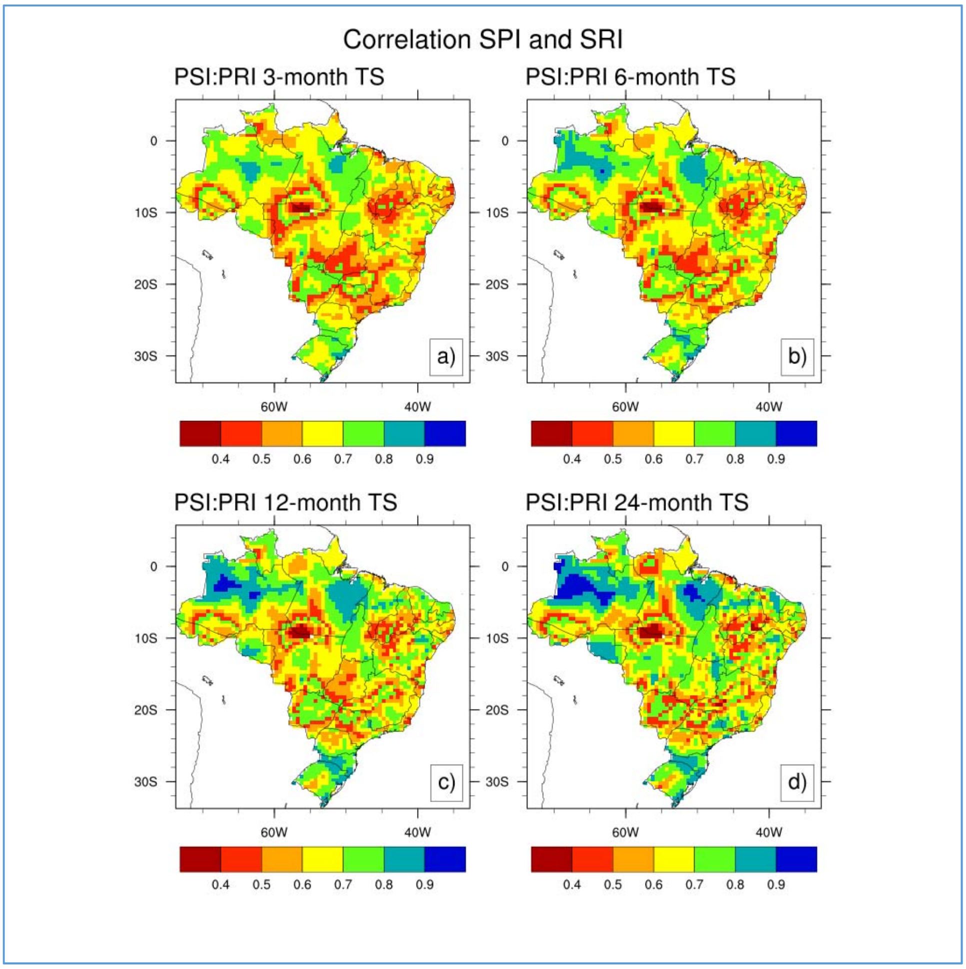

Figure 14: The correlation between rainfall anomalies (SPI) and runoff anomalies (SRI) for the 1950-2013 period at (a) 3-month, (b) 6-month, (c) 12-month and (d) 24-month timescale.

The differences between the SPI and SRI are larger at short-timescales than those at long-timescales. As illustrated in Figures 15 and 16 by time series of the SPI and SRI for 3-month and 12-month timescales, at selected grid-cells (5.0^{o}S, 49.625^{o}W), (4.375^{o}S, 63.625^{o}W), (11.125^{o}S, 49.625^{o}W) and (27.75^{o}S, 51.5^{o}W), representing (a) northern, (b) north-western, (c) central and (d) southern Brazil, respectively. In case of drought at 3-month timescale, the indices attain values more frequently than the 12-month indices and the SPI recovers to above zero (normal levels) more frequently than the SRI. The SPI shows spells of rainfall deficit that are insufficient to declare hydrological drought impacts/conditions, a reality reflected in the non-recovery of the SRI at these timescales. Due to hydrologic delays, for example associated with soil-moisture (or snow where applicable) the SPI gets desynchronized from the response of land surface to the rainfall anomalies. Therefore, runoff variations at short-timescales are more determined by the current rainfall and the immediate previous months than longer time periods (i.e., relatively short memory). This is consistent with previous results (Vicente-Serrano and L´opez-Moreno, 2005, Patel et al., 2007).

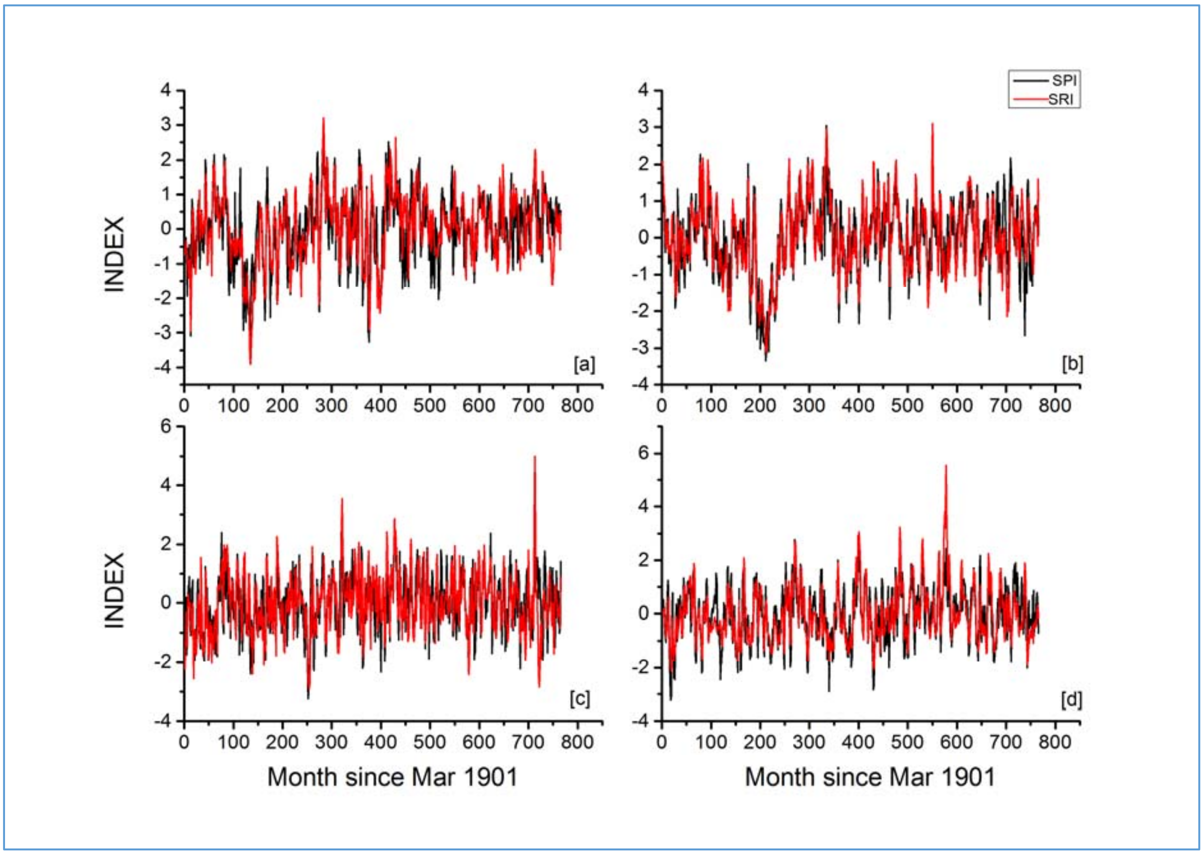

Figure 15: Time series of the SPI and SRI at 3-month timescale for the 1901-2013 period at grid-cells representing (a) northern (5.0°S, 49.625°W), (b) north-western (4.375°S, 63.625°W), (c) central (11.125°S, 49.625°W) and (d) southern (27.75°S, 51.5°W) sectors of Brazil.

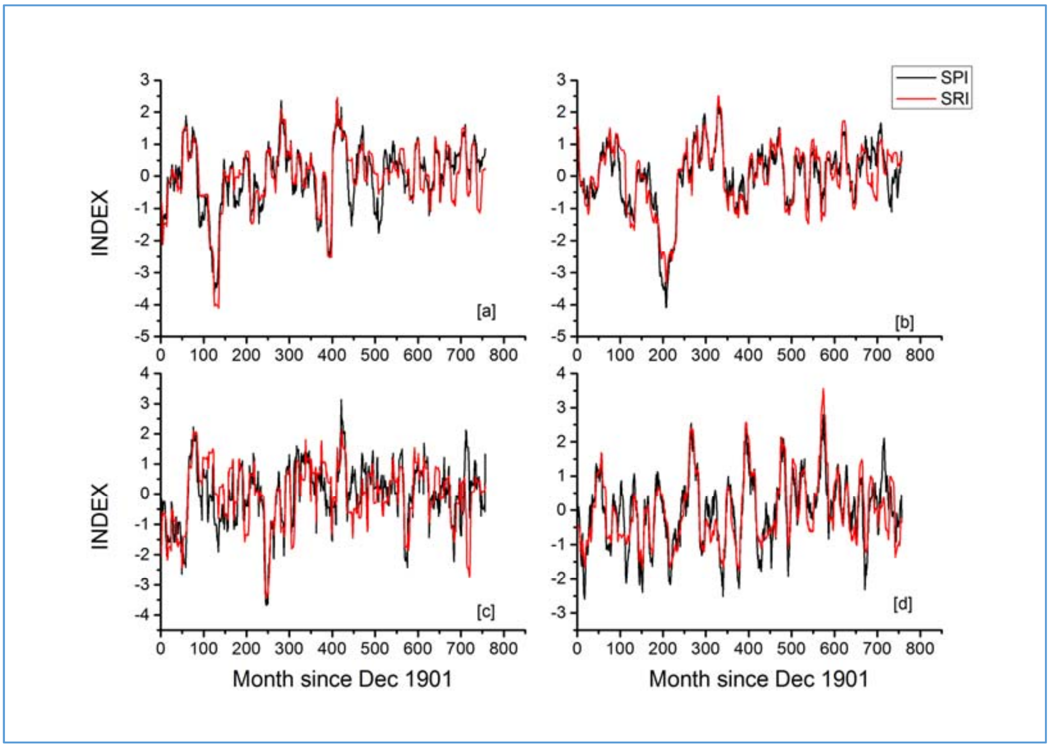

Figure 16: Time series of the SPI and SRI at 12-month timescale for the 1901-2013 period at grid-cells representing the (a) northern (5.0°S, 49.625°W), (b) north-western (4.375°S, 63.625°W), (c) central (11.125°S, 49.625°W) and (d) southern (27.75°S, 51.5°W) sectors of Brazil.

Table 2 lists the correlation between SPI and SRI, and their respective 1st order autocorrelation at selected grid-cells to demonstrate the effects of timescale and rainfall regime. The higher 1st order correlation in SRI than in SPI at short-timescales (3-month and 6-month), shows that SRI is less variable from month to month than the SPI. This can be attributed to the effect of soil-moisture retention (or snow storages) in regulating runoff. On the other hand, at 12-month timescale, the integration over the entire water-year is longer than most influences of the hydrological modulation. However, much longer integrations can accumulate values that are well past in time, thus may no longer have effect on current runoff conditions but relevant to soil-water content and river discharge in headwater areas. Medium timescale droughts can be reflected in reservoir storages and discharge in the medium course of the rivers, while long time-scale droughts relate to variations in groundwater storage as demonstrated elsewhere, e.g., (2005, Patel et al., 2007). The correlation of the SPI and SRI is lower in areas of low rainfall, for example in the central areas of Brazil than in wet regions (the northern, north-western and southern areas), as shown in Table 2.

Table 2: Correlation between SPI and SRI and their 1^{st} order auto-correlation for grid-cells representing the northern (5.0^{o}S, 49.625^{o}W), north-western (4.375^{o}S, 63.625^{o}W), central (11.125^{o}S, 49.625^{o}W) and southern (27.75^{o}S, 51.5^{o}W) sectors of Brazil.

Location	Correlation between SPI and SRI				1^{st} order auto-correlation							
					SPI				SRI			
	TS3	TS6	TS12	TS24	TS3	TS6	TS12	TS24	TS3	TS6	TS12	TS24
Northern	0.78	0.84	0.87	0.90	0.74	0.89	0.96	0.98	0.84	0.92	0.98	0.99
North-Western	0.84	0.86	0.88	0.91	0.80	0.92	0.97	0.99	0.88	0.94	0.98	0.99
Central	0.73	0.72	0.73	0.75	0.59	0.77	0.90	0.96	0.70	0.82	0.95	0.98
Southern	0.81	0.83	0.86	0.88	0.73	0.88	0.95	0.97	0.87	0.94	0.98	0.99

3.5 Association of Brazil rainfall anomalies with major climate variability drivers

The correlation between Brazil rainfall anomalies with the 4 major climate variability drivers (ONI, IOD, TADI and IPO) demonstrated similar spatial patterns for all the 4 timescales. Figure 17 shows the pattern of correlations and their respective levels of significance for the 12-month timescale. This pattern is the same for all the other timescales (not shown). In Figure 17a-b, the pattern indicates that warm ONI (El Niño) conditions are favourable to negative rainfall anomaly over half of Brazil to the north; while the negative rainfall anomalies over the other half to the south is favoured by cold ONI (La Niña) conditions. Figure 17c-d shows that over almost the entire country, IOD in negative mode is conducive to negative rainfall anomaly except for the extreme south areas and the extreme northwest areas, and vice versa. However, the low correlation and poor significance levels indicate that most probably IOD has little or no direct link to rainfall anomalies over Brazil. Figure 17e-f shows that TADI in negative mode favours negative rainfall anomalies over the northern half and the extreme south of Brazil and the converse is true elsewhere. In Figure 17g-h, the pattern of IPO association with rainfall anomalies is a mirror image of the pattern of ONI.

There has been a great deal of research in recent years on the role of interacting systems and teleconnections associated with drought occurrences (Swetnam and Betancourt, 1998, Cook et al., 1999 , Cordery and McCall, 2000, Murphy and Timbal, 2008). The influence of such climate variability drivers largely depends on their modes in concurrent years (Behera et al., 2006). This is the main source of uncertainty in the prediction of climatic extremes including droughts (Kane, 1997).

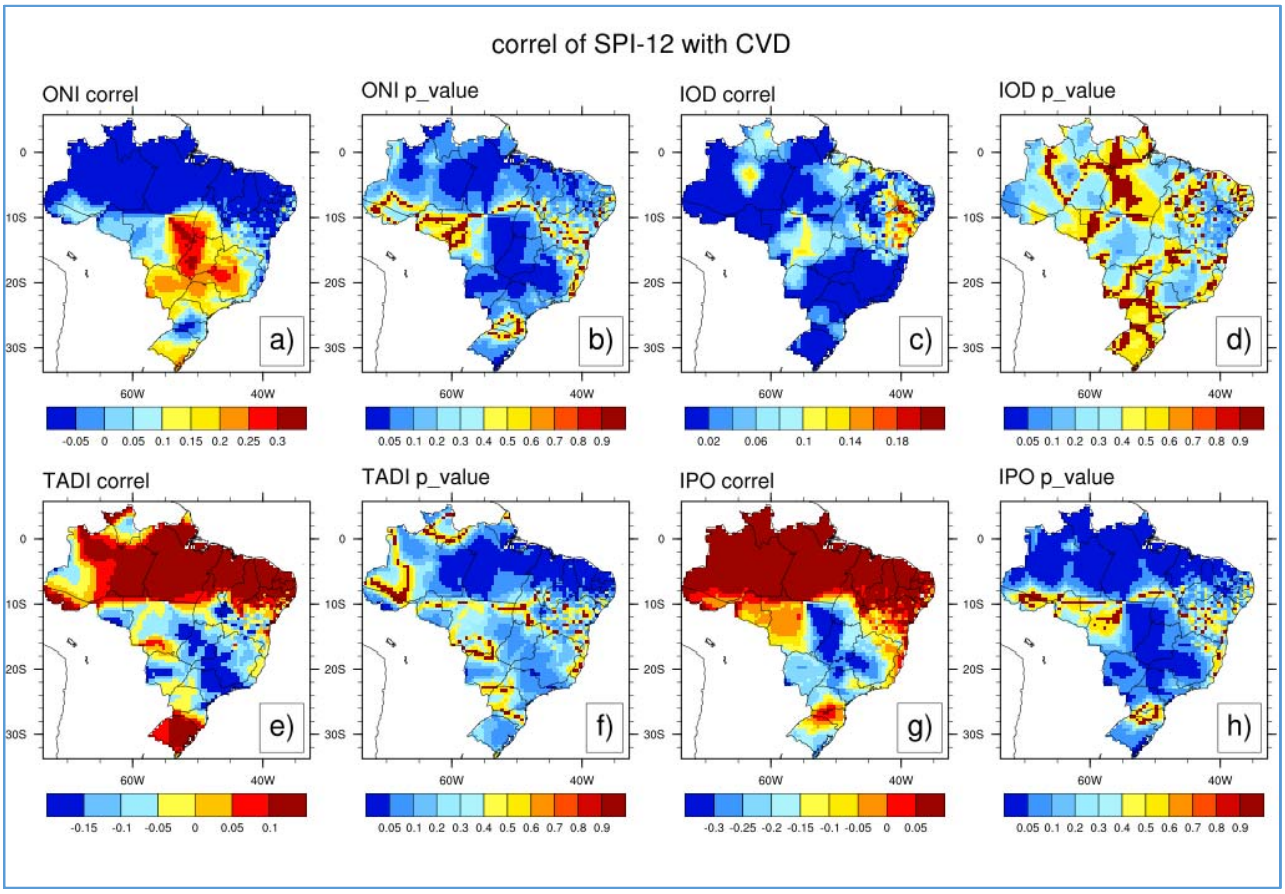

Figure 17: Correlation of rainfall anomalies (in terms of 12-month SPI) with 4 climate variability drivers (CVD), (a-b) Oceanic Niño Index (ONI), (c-d) Indian Ocean Dipole (e-f) Tropical Atlantic Dipole index (TADI) and (g-h) Inter-decadal Pacific Oscillation (IPO).

4. Conclusions

The estimation of long-term statistics of attributes of drought characteristics forms the basis of risk-management policy development in the context of living with drought. This is in view of taking a more realistic approach in the management of drought impacts rather disaster-based short term solutions alone. This study analysed a sequence of SPI-derived drought events on a

~25km x 25km grid over Brazil for a period covering 112 years to provide desirable information on the attributes of drought characteristics. The study found the following:

1. Despite the drought events being solely driven by rainfall data, the application of SPI provided drought events at different timescales, which by inference identify various operational drought types useful for various aspects. For example, short-timescale droughts relate to agricultural drought and river discharge in headwater areas, medium-timescale droughts reflect levels of reservoir storages and discharge of the rivers, and long-timescale droughts relate to groundwater storage. This information is vital for management of both water and agricultural aspects of Brazil within the concept of "living with drought".

2. Similar frequencies of severe and extreme droughts at short-timescales were observed across Brazil (1 in 12 and 1 in 66 years, respectively). Apparently, at medium and long-timescales, the frequency of severe droughts is about (1 in 20 years) in northern Brazil and 1in 10 years in the south. On the contrary, the frequencies of extreme droughts are on the average slightly higher (1 in 9 years) over northern Brazil than in the south (1 in 12 years).

3. The 50th percentile values of intensity droughts were found to cause moderately dry conditions, except for the long-timescales, while those of the 90th percentile were found to be associated with extreme dry conditions. Half of the time, droughts at short-

timescales on the average have duration of 3-5 months. The 90th percentile values of drought duration range from 4 to 10 months.

4. Generally, there is no evidence of significant (α = 0.05) trend in drought frequency, intensity and duration over the last 11 decades for droughts at all 4 timescales considered.
5. Drought areal-extent show increasing trends over Brazil (3.4%/decade) for both 3-month and 6-month timescales. The increasing trends for the 12-month and 24-month timescales are relatively smaller (2.4% /decade and 0.5%/decade, respectively).

In the absence of skilled dynamic and empirical models capable of incorporating major climate variability drivers (e.g., ONI, IOD, TADI, and IPO), prediction of drought characteristics remains a challenge. Therefore, the long-term statistics approach to inform strategic drought managers and policy makers is important. Such information is fundamental for the implementation of programmes towards drought risk management strategies. In addition, this information is vital for administration purposes for a better interpretation of climate variability and baseline for change perception, when every drop counts.

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