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# Evaluation of drought indices at interannual to climate change timescales: a case study over the Amazon and Mississippi river basins

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## Abstract

The present study compares three meteorological drought indices (scPDSI, SPI and SPEI respectively) and their ability to account for the variations of annual mean river discharge on both interannual and climate change timescales. The Standardized Runoff Index (SRI) is used as a proxy of river discharge. The Mississippi and Amazon river basins provide two contrasted testbeds for this analysis. All meteorological drought indices are derived from monthly 2-meter temperature and/or precipitation, using either gridded observations or outputs of a global climate model. The SPI based solely on precipitation is not outperformed by the SPEI (accounting for potential evapotranspiration) and the scPDSI (based on a simplified water balance) at detecting interannual SRI variations. Under increasing concentrations of greenhouse gases, the simulated response of the areal fraction in drought is highly index-dependent, suggesting that more physical water balance models are needed to account for the impact of global warming on hydrological droughts.


## 1 Introduction

Droughts are recurrent natural manifestations of climate variability that have plagued civilizations throughout history. They are often commonly classified into three types – meteorological, agricultural and hydrological – depending on which variable – respectively precipitation, soil moisture and river flow – is below normal conditions (Dai, 2011a). Meteorological drought often precedes and causes other types of droughts. Meteorological indices are therefore used not only for monitoring drought at regional to global scales, but also for anticipating their potential impacts on agriculture and water resources.

Several empirical meteorological drought indices have been proposed and applied at regional to global scales over the second half of the 20th century (e.g. Heim, 2002). Nevertheless, evidence is building that human-induced climate change is perturbing





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the global hydrological cycle (e.g. Trenberth, 2011), making necessary to analyse the validity of such indices in a warmer climate. While most 21st century climate scenarios project a global increase in the frequency, intensity and duration of droughts (Sheffield and Wood, 2008), the response is still very uncertain at the regional scale and is not necessarily consistent from one metric to the other (e.g. Burke and Brown 2008).

In the 4th IPCC report, the 20th century multi-decadal variations of drought were mainly discussed on the basis of the Palmer Drought Severity Index (PDSI, Palmer, 1965). This standardized index measures the departure of soil moisture using a simplified surface water balance model. It requires globally available precipitation ($P$) and temperature data as input for the calculation of potential evapotranspiration (PET) with Thornthwaite's (1948) equation, as well as the soil water field capacity. Analysis of global PDSI maps indicates that drought has generally increased throughout the 20th century (Dai et al., 2004).

The PDSI has been however criticized in several respects (e.g.Guttman, 1998; Vicente-Serrano et al., 2011). Some drawbacks were addressed by Wells et al. (2004) who proposed a self calibrated PDSI (scPDSI) which will be used in the present study. An alternative PDSI has also been proposed using a Penman (1948) rather than Thornthwaite approach for PET, without much influence on the results (Van der Schrier et al., 2011). Finally, it has been argued that the PDSI cannot account explicitly for the multi-scale nature of drought (Vicente-Serrano et al., 2010). In contrast, the Standardized Precipitation Index (SPI) of McKee et al. (1995) is a simple multi-scale index computed as a standardized transform of cumulative precipitation over a given period. More recently, Vicente-Serrano et al. (2010) have developed the Standardized Precipitation Evapotranspiration Index (SPEI) by applying a similar transform on cumulated $P$ minus PET.

The superiority of this new index compared to the PDSI is still a matter of debate (Dai, 2011b). In spite of the criticisms of Guttman (1998) or Vicente-Serrano et al. (2010), the PDSI has been evaluated successfully at the regional or basin scale against both soil moisture and river discharge (Dai et al., 2004). Moreover, it compares relatively well





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with the 12-month SPEI (Vicente Serrano et al., 2011). There is therefore a need for more comprehensive intercomparisons as well as for objective evaluation against independent data, using either observations or climate model outputs which are globally available over the whole 20th century.

The present study aims at comparing the behavior of three meteorological drought indices (scPDSI, SPI and SPEI) at both interannual and climate change timescales. In line with the implicit dominant timescale of the PDSI (e.g. Burke and Brown, 2008), only 12-month SPI and SPEI will be here considered. Moreover, only annual mean values will be analyzed in order to focus on major persistent droughts and reduce the uncertainties associated with dams, irrigation and/or the lag between meteorological and hydrological droughts. Two large and contrasted river basins, Amazon and Mississippi, have been selected as a testbed.

## 2 Datasets, model and methods

### 2.1 Observed and simulated drought indices

Monthly precipitation and temperature observations (see Table 1) were first interpolated onto the 1.4° CNRM-CM5 (Voldoire et al., 2012) horizontal grid. On each grid cell, the scPDSI and the 12-month SPI and SPEI (hereafter SPI12 and SPEI12 respectively) were computed following the original algorithms proposed by Wells et al. (2004), McKee et al. (1995) and Vicente-Serrano et al. (2009) respectively. Cumulated $P$ was fitted with a gamma function, while a log-logistic function was preferred for $P$ minus PET (Vicente-Serrano et al., 2009) for the SPEI. While the simple Thornthwaite equation was used to compute PET from temperature and latitude for SPEI (hereafter SPEI_th) and scPDSI, another empirical formulation (Hargreaves and Samani, 1982) accounting more accurately for the role of solar radiation was tested for SPEI (hereafter SPEI_hg). More sophisticated formulations such as Penman-Monteith have not been tested given the lack of global observations of solar radiation over the whole 20th century. No attempt





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has been made to use Hargreaves in the sc-PDSI calculation, which is more sensitive to precipitation and soil moisture limitation on actual ET (Van der Schrier et al., 2011).

For all indices, annual mean values were averaged from January to December. Basin average indices were calculated and compared with Global Runoff Data Center (GRDC) annual mean river discharge observations at the basin outlet. Normalization was here made in each grid cell before spatial averaging, but the reverse approach was also tested and led to similar conclusions. Model-derived drought indices were computed with the same algorithms applied onto monthly outputs from a 5-member ensemble of 1850–2100 simulations based on the CNRM-CM5 climate model (Voldoire et al., 2012).

Hydrological drought has been here defined using the Standardized Runoff Index (hereafter SRI) proposed by Shukla and Wood (2008), i.e. applying the same algorithm as for SPI12 but on the 12-month cumulated runoff produced by the ISBA land surface model (part of the coupled CNRM-CM5 model). This was done using monthly runoff from both a global 1951–2006 off-line simulation of the ISBA-TRIP land surface model (part of the CNRM-CM5 model) driven by bias-corrected reanalyses (Alkama et al., 2011) and the ensemble of coupled CNRM-CM5 climate simulations. The off-line simulated SRI12 (Fig. 1) is indeed highly correlated with in situ river discharge observations over both Amazon and Mississippi, and therefore provides a meaningful hydrological benchmark for both observed and simulated meteorological drought indices.

Finally, a simulated "Standardized Precipitation Actual Evapotranspiration Index" (SPAEI) was also calculated by replacing PET by ET in the SPEI algorithm, in order to highlight the consequences of the PET approximation.

## 2.2 Statistical analysis

Given the global warming influence on the hydrological cycle, all basin-averaged indices have been detrended using spline functions (e.g. Ribes et al., 2010) before comparing their interannual variations on the basis of correlation with the hydrological





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SRI12 drought index. The Clayton Skill Score, based on the probability for each index to be either above or below a given percentile of the distribution, has also been used to assess the ability to detect major hydrological droughts. This skill score is simply computed as the difference between two conditional probabilities: $\mathrm{CSS} = \frac{A}{A+B} - \frac{C}{C+D}$ where $A$ is the number of meteorological droughts detected by the index that correspond to hydrological droughts (number of hits), $B$ is the number of meteorological droughts that do not correspond to hydrological droughts (number of false alarms), $C$ is the number of no-drought forecasts corresponding to hydrological droughts (number of misses), and $D$ is the number of no-drought forecasts corresponding to no-drought hydrological events (number of correct rejections). For a perfect detection, $B = C = 0$, so that $\mathrm{CSS} = 1$.

The CSS allows us to focus on particular events. Unfortunately, the relatively short river discharge timeseries is a strong limitation to our study that will focus on the 20th percentile of the distribution rather than on extreme events. For the observed annual mean timeseries, correlation and CSS have been calculated over a 49-yr period (1951–1999) with available river discharge data. For the sake of comparison, similar scores have been computed over 49-yr sliding windows for each 1850–2100 CNRM-CM5 climate simulations (the 20th percentile being estimated over the same 1951–1999 period as in observations). In addition, scores of simulated indices have been also estimated over the whole 251-yr integrations, using 20th but also 10th and 5th percentiles.

Finally, the raw timeseries (i.e. not detrended) of the simulated drought indices have also been used to compute the fraction of each basin experiencing a 12-month drought, and its evolution from 1850 to 2100 under the RCP8.5 climate change scenario (i.e. a radiative concentration pathway corresponding to a $8.5\,\mathrm{W\,m^{-2}}$ radiative forcing at the end of the 21st century).

## 3 Results

### 3.1 Evaluation of meteorological drought indices against hydrological benchmark index

Besides observed and ISBA-simulated variations of annual mean discharge at Obidos (Amazon) and Vicksburg (Mississippi), Fig. 1 shows the detrended timeseries for the various meteorological indices, as well as the ISBA-derived SRI12 for further comparison over years without discharge observations (over the Amazon basin). Both correlations and CSS are slightly higher over the Amazon than over the Mississippi. Such a difference could be partly related to the different seasonality of precipitation and the possible contribution of early winter snowfall to the following year annual mean runoff in the mid-latitudes. Over the Amazon, the SPEI12_hg shows the best correlation with the SRI12 benchmark, closely followed by the SPEI12_th and SPI12. However, such differences are not significant and CSS scores are the same for all three indices. Over the Mississippi, scores are also very close and longer timeseries would be useful to reach more robust conclusions about the relative skill of the different meteorological indices.

For this purpose, correlations and CSS have also been estimated over 49-yr sliding windows from our 5-member ensemble of 1850 to 2100 climate simulations, with model-derived SRI12 taken as a reference. Results are summarized in box-and-whisker plots (Fig. 2). In line with observations, all model-derived meteorological indices are relatively skillful over both river basins. Ranking them is particularly difficult over the Mississippi where differences in mean scores are not significant. Results are more contrasted over the Amazon where SPI and SPEI_hg outperform other indices. This suggests that the details of the index computation (SPEI_hg versus SPEI_th) are as important as the choice of the index (SPEI vs. SPI or PDSI).

How sensitive are our CSS scores to the quantile chosen as a threshold for drought definition? Considering now moderate (*q20*), severe (*q10*) and extreme (*q5*) droughts over the whole 1850–2100 period (Table 2), the simple SPI index is the best proxy of

12-month hydrological droughts. SPEI scores are however relatively close and again improve when PET is calculated with Hargreaves in place of Thornthwaite equation. The scPDSI shows less skill than the other indices which might be due to its lack of specific timescale.

In summary, precipitation remains the main driver of runoff at the interannual timescale and accounting for PET (for SPEI) or even a simplified water balance (for sc-PDSI) does not improve the detection of 12-month hydrological droughts. As shown in Table 2, such a conclusion is not specific to the Amazon and Mississippi river basins, but also holds when averaging scores over all land grid points in the CNRM-CM5 model. Note however that the apparent superiority of the SPI index might be timescale-dependent and would not necessarily hold for agricultural rather than hydrological droughts as a reference.

### 3.2 Climate change timescale

Moving to the raw model outputs, Fig. 3 shows the projection of the areal fraction of the Amazon and Mississippi basins in moderate, severe and extreme drought conditions (respectively defined under the 20th, 10th and 5th percentile estimated over the whole 1850–2100 period). Results obtained with the SRI12 benchmark are compared to the fractions derived from each meteorological index. Bold lines represent the ensemble mean value for each percentile. The envelope is defined by the minimum and maximum values among the five members for severe drought only (10th percentile), as an indication of the internal variability of the CNRM-CM5 climate model.

For SRI12, CNRM-CM5 under the RCP8.5 concentration scenario projects a slight increase in the areal fraction of the Amazon basin touched by hydrological drought, while the Mississippi basin shows a more dramatic increase. Such a response is not necessarily consistent with the contrasted long-term variations derived from the meteorological drought indices. The SPI12 behaves as a better proxy of SRI12 than scPDSI and SPEI12 over the Amazon basin where precipitation change seems to control the long-term evolution of hydrological droughts and surface warming remains of marginal





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control. Conversely, the SPI12 evolution is in contradiction with the SRI12 evolution over the Mississippi basin, where increased evapotranspiration seems to exceed increased precipitation and lead to more frequent and/or extended hydrological droughts at the end of the 21st century. This result highlights the SPI limitations, where and when temperature trends become strong enough to alter evapotranspiration without or despite changes in precipitation. Nevertheless, accounting for changes in PET does not necessarily solve the problem, as emphasized by Fig. 4. Indeed, the SPEI response to global warming is strongly dependent on PET calculation. The strong sensitivity shown by SPEI12_th over both basins shows that Thornthwaite's formula is not adequate for climate change studies and should be at least superseded by more robust approaches (e.g. Hargreaves or Penman-Monteith). Despite the presumably weaker sensitivity of the PDSI index to PET calculation (Van der Schrier et al., 2011), it is likely that the large increase of the areal fraction in drought obtained with this index is also due to the simplistic PET calculation in the original algorithm. Over the Mississippi, the SPAEI12, accounting for actual ET, shows more consistency with the "target" SRI12 than the other indices.

## 4 Discussion and conclusion

The present study aimed at comparing three empirical drought indices, first in their skill to detect annual hydrological droughts, then in their response to anthropogenic climate change.

Using the SRI as a reference for hydrological drought, the simple SPI index, based solely on precipitation, was not outperformed by more sophisticated empirical indices also using temperature inputs. Such a conclusion should be however tempered. First, it would not necessarily hold for agricultural rather than hydrological droughts. Then, it might also depend on the selected timescale and on the details of the calculation. Normalization is a non-linear transform which raises severe issues for both spatial and time averaging. Here, we have considered all drought indices as global gridded and





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monthly datasets that can be averaged in both space and time. At the basin scale, averaging the meteorological variables before of after normalization will however lead to different results. In the present study, this issue was alleviated since spatial variability is relatively smooth on annual timescale and the reference hydrological index was a basin-averaged SRI rather than the basin outlet river discharge (though both are strongly correlated on a 12-month timescale).

This normalization versus averaging issue also emphasizes the limitations of the empirical drought indices. While the SPI or SPEI timescale can be fitted for each basin to optimize the correlation with monthly river discharge (Vicente-Serrano et al., 2012), this fitting should also vary with the location of precipitation within the basin and at least be season-dependent. Moreover, as far as the PDSI is concerned, it is questionable to compute a basin-scale water balance using a basin-average water holding capacity.

Moving to climate change, and in line with the conclusions of Burke and Brown (2008) and Burke (2011), our study emphasizes that drought projections are strongly index-dependent given the differing impact of temperature in their calculation. While the SPEI was recently proposed as a drought index sensitive to global warming (Vicente Serrano et al., 2010), it shows a stronger drying of the Amazon and Mississippi basins than indicated by our reference hydrological index. This discrepancy is less pronounced when estimating PET with Hargreaves, especially for Mississippi, showing that precipitation is not the only driver of the long-term drought variations.

Besides satellite observations (e.g. Anderson et al., 2011), the main alternative for drought monitoring and projections is the use of process-oriented LSMs which can be either driven by observed atmospheric forcings (e.g. Sheffield and Wood, 2007) and bias-corrected climate scenarios or directly coupled to global climate models (e.g. Sheffield and Wood, 2008). Given the intrinsic uncertainties related to the various physical and biological processes represented in such LSMs (e.g. Betts et al., 2007), a multi-model approach is however strongly encouraged.





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**Table 1.** Gridded datasets and in situ river discharge observations and/or reconstructions.

| | 20th century | 1850–2100 |
|---|---|---|
| Data | 1° monthly precipitation: GPCC version 5 (Rudolf et al., 2011)<br>0.5° monthly surface air temperature: CRU TS.3 (Mitchell and Jones, 2005)<br>Monthly river discharge: GRDC (http://www.bafg.de/GRDC)<br>1° runoff and river discharge derived from off-line simulations (1951–2006): SURFEX hydrological system based on the ISBA land surface model and the TRIP river routing model (Decharme and Douville, 2007) | 1.4° CNRM-CM5 historical simulation and RCP8.5 climate change scenario (5 members) |





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**Table 2.** Results for correlation and CSS between meteorological drought indices and the Standardized Runoff Index 12. Scores were calculated for average indices over the Amazon and Mississippi watersheds, and for grid points over the globe (lon: −180° E, +180° W; lat: −60° S, +60° N). The CSS was calculated using the 5th, 10th and 20th percentiles over 1851–2100 to define drought. Mean and standard deviation (sd) for the members of the scenario RCP8.5 are shown. Highest (bold) and lowest (italics) mean values are also shown.

| | | Amazon | | Mississippi | | Global | |
|---|---|---|---|---|---|---|---|
| | | mean | sd | mean | sd | mean | sd |
| Correlation | | | | | | | |
| | SPI12 | **0.97** | 0.001 | **0.88** | 0.023 | **0.89** | 0.014 |
| | SPEI12_th | 0.89 | 0.017 | 0.86 | 0.027 | 0.76 | 0.064 |
| | SPEI12_hg | 0.96 | 0.006 | 0.88 | 0.023 | 0.84 | 0.036 |
| | scPDSI | *0.88* | 0.004 | *0.84* | 0.030 | *0.75* | 0.033 |
| CSS | | | | | | | |
| *q20* | SPI12 | **0.84** | 0.071 | 0.68 | 0.082 | **0.69** | 0.052 |
| | SPEI12_th | 0.70 | 0.050 | 0.64 | 0.129 | 0.56 | 0.081 |
| | SPEI12_hg | 0.82 | 0.059 | **0.69** | 0.124 | 0.64 | 0.065 |
| | scPDSI | *0.68* | 0.072 | *0.63* | 0.070 | *0.53* | 0.068 |
| *q10* | SPI12 | **0.79** | 0.053 | **0.61** | 0.101 | **0.65** | 0.073 |
| | SPEI12_th | 0.65 | 0.077 | *0.55* | 0.084 | 0.52 | 0.095 |
| | SPEI12_hg | 0.77 | 0.038 | 0.59 | 0.065 | 0.59 | 0.084 |
| | scPDSI | *0.64* | 0.049 | 0.61 | 0.047 | *0.49* | 0.088 |
| *q5* | SPI12 | **0.77** | 0.089 | **0.56** | 0.092 | **0.59** | 0.105 |
| | SPEI12_th | *0.66* | 0.068 | *0.53* | 0.068 | 0.47 | 0.118 |
| | SPEI12_hg | 0.72 | 0.092 | *0.53* | 0.068 | 0.55 | 0.112 |
| | scPDSI | *0.66* | 0.106 | *0.53* | 0.120 | *0.44* | 0.121 |





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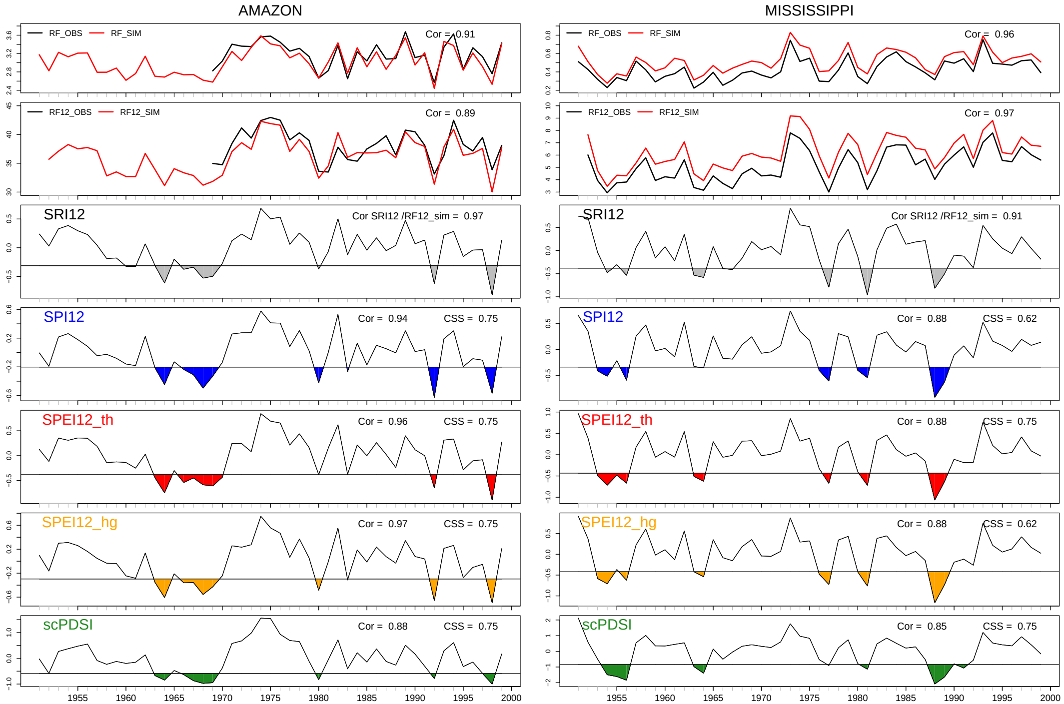


**Fig. 1.** Annual mean time series from 1951 to 1999 of river flow (RF mm day$^{-1}$), cumulated river flow over 12 months (RF12 mm day$^{-1}$), detrended SRI12, and detrended meteorological drought indices (SPI12, SPEI12_th, SPEI12_hg and scPDSI). The correlation and the CSS scores between SRI12 and each meteorological index are indicated in the top right corner of each plot. For each index, droughts are defined under the twentieth percentile and are shaded.

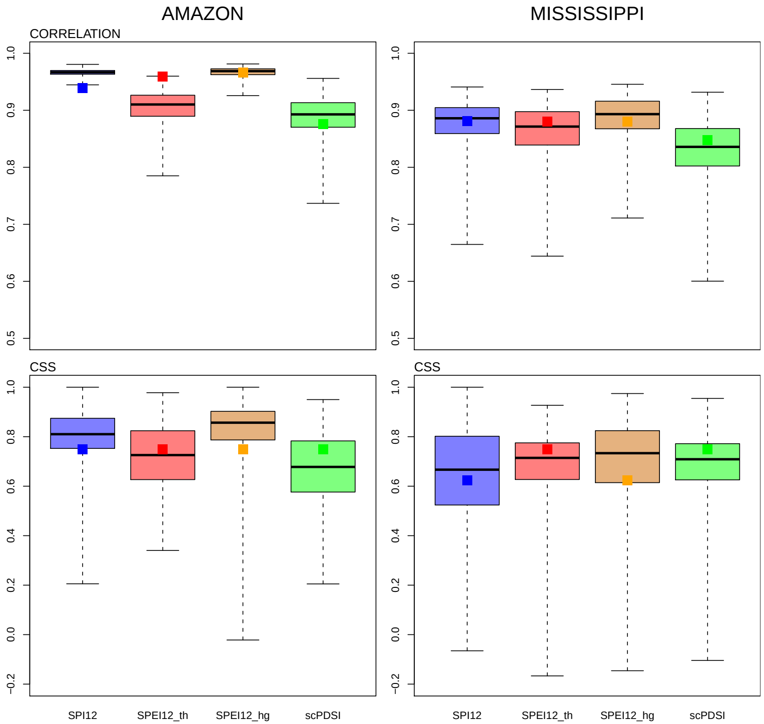


**Fig. 2.** Box and whisker plot of the sliding correlations and the CSS_20 calculated for the five members of the RCP8.5 scenario from 1850 to 2100 over a 49-yr time span for the Amazon and Mississippi watersheds. The boxes represent the 25th and the 75th percentile, the line the mean value, and the whiskers the minimum and the maximum values of the ensemble spread. The smaller squares indicate results obtained from observations (1951–1999).





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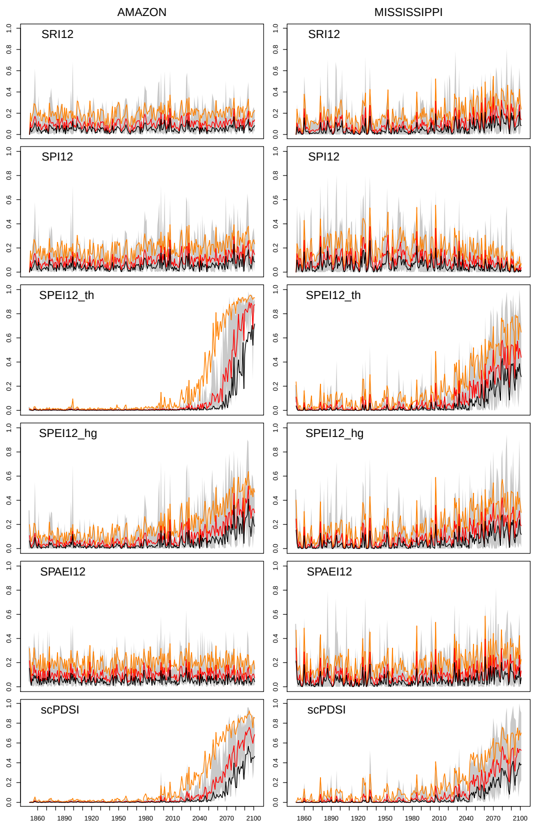


**Fig. 3.** Time series from 1850 to 2100 of the ensemble mean value of the areal fraction in drought condition in the Amazon and Mississippi basins. Moderate, severe and extreme droughts are defined locally as below the 20th (orange), the 10th (red) and the 5th (black) percentile. The envelop around the red line is defined by the minimum and maximum values among the five members.





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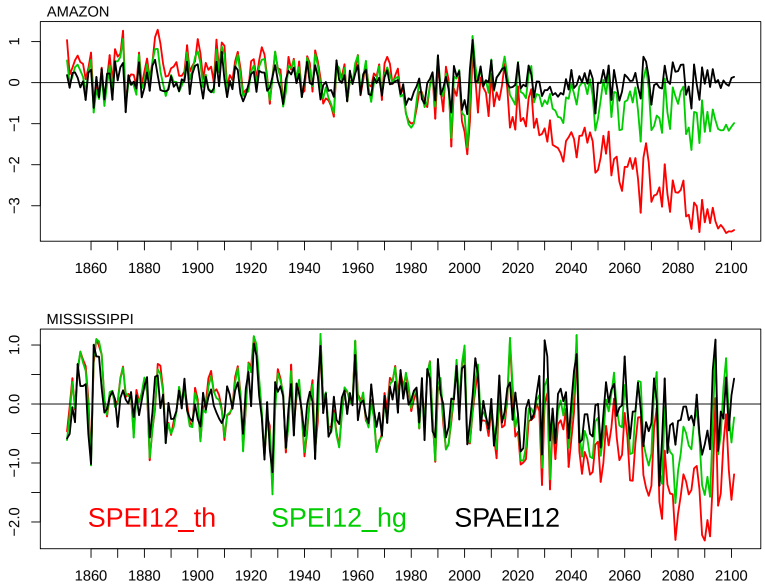


**Fig. 4.** Raw SPEI12 time series averaged over the Amazon (upper panel) and the Mississippi (lower panel) watersheds for one member of the CNRM-CM5 1850–2100 simulations.





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