Assessment of the global coherence of different types of droughts in model simulations under a high anthropogenic emission scenario

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Abstract

This study provides a global analysis of drought metrics obtained from several climatic, hydrologic and ecological variables in a climate change framework using CMIP6 model data. A comprehensive analysis of the evolution of drought severity on a global scale is carried out for the historical experiment (1850-2014) and for future simulations under a high emissions scenario (SSP5-8.5). This study focuses on assessing trends in the magnitude and duration of drought events according to different standardised indices over the world land-surface area. The spatial and temporal agreement between the different drought indices on a global scale was also evaluated. Overall, there is a fairly large consensus among models and drought metrics in pointing to drought increase in southern North America, Central America, the Amazon region, the Mediterranean, southern Africa and southern Australia. Our results show important spatial differences in drought projections, which are highly dependent on the drought metric employed. While a strong relationship between climatic indices was evident, climatic and ecological drought metrics showed less dependency over both space and time. Importantly, our study demonstrates uncertainties in future projections of drought trends and their interannual variability, stressing the importance of coherent hydrological and plant physiological patterns when analysing CMIP6 model simulations of droughts under a warming climate scenario.

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Abstract

This study provides a global analysis of drought metrics obtained from several climatic, hydrologic and ecological variables in a climate change framework using CMIP6 model data. A comprehensive analysis of the evolution of drought severity on a global scale is carried out for the historical experiment (1850-2014) and for future simulations under a high emissions scenario (SSP5-8.5). This study focuses on assessing trends in the magnitude and duration of drought events according to different standardised indices over the world land-surface area. The spatial and temporal agreement between the different drought indices on a global scale was also evaluated. Overall, there is a fairly large consensus among models and drought metrics in pointing to drought increase in southern North America, Central America, the Amazon region, the Mediterranean, southern Africa and southern Australia. Our results show important spatial differences in drought projections, which are highly dependent on the drought metric employed. While a strong relationship between climatic indices was evident, climatic and ecological drought metrics showed less dependency over both space and time. Importantly, our study demonstrates uncertainties in future projections of drought trends and their interannual variability, stressing the importance of coherent hydrological and plant physiological patterns when analysing CMIP6 model simulations of droughts under a warming climate scenario.

Keywords: Climate change, drought projections, CMIP6 simulations, model uncertainty.

1. Introduction

Assessment of future drought projections is at the forefront of scientific debate in the current research on climate, hydrology, agriculture, and ecology. This is simply due to the multiple dimensions of droughts, which cause strong complexity for drought assessment and quantification (Lloyd-Hughes, 2014; Douville *et al.*, 2021). In addition, the strong environmental and socioeconomic implications of drought changes in future climate scenarios adds more complexity to this debate (Van Loon *et al.*, 2016; Xu *et al.*, 2019; Naumann *et al.*, 2021).

In order to robustly assess future changes in drought severity, we must refer to different types of drought. This is fundamental to properly evaluate the impacts associated with drought in future climates. Generally, the concepts of meteorological drought (precipitation deficits), agricultural droughts(crop failure or yield decrease), ecological droughts (damages in natural vegetation, reduced photosynthesis activity, and carbon uptake and increased plant mortality), and hydrological droughts (reductions in the availability of water in different sources such as reservoir storages, streamflow and groundwater) are used commonly to refer to drought types. These types are largely impacted by different processes and physical and ecological implications (Wilhite and Buchanan-Smith, 2005; Lobell, 2014; Vicente-Serrano *et al*, 2020b; Douville *et al*, 2021).

In the literature, a wide spectrum of studies characterised drought projections on the global scale using model simulations of various climatic, hydrological, and vegetation variables under different future climates scenarios (e.g. Cook *et al*., 2014, 2020; Martin, 2018; Lu*et al*., 2019; Ukkola*et al*., 2020; Vicente-Serrano*et al*., 2020a; Zhu and Yang, 2021; Papalexiou*et al*., 2021; Zhao and Dai, 2021; Ridder*et al*., 2022; Zeng*et al*., 2022). Nonetheless, most of these studies focused on metrics directly simulated by different Coupled Model Intercomparison Projects (CMIP) since they allow to directly evaluate drought impacts on a variety of agricultural, ecological, and hydrological systems (Quiring and Papakryiakou, 2003; Hlavinka *et al.*, 2009;

Vicente-Serrano *et al.*, 2012; Stagge *et al.*, 2015a; Bachmair *et al.*, 2016, 2018; O'Connor *et al.*, 2022).

In the literature, the most widely used drought metrics for drought monitoring and impact assessment are synthetic indices that combine precipitation and atmospheric evaporative demand (AED), allowing for a direct quantification of drought severity and drought extent (Vicente-Serrano *et al.*, 2010; van der Schrier *et al.*, 2013; Tomas-Burguera *et al.*, 2020a; Dai, 2021), as well as their impacts on ecosystems (Bachmair *et al.*, 2015). For future simulations, different studies analysed drought projections based on these indices, employing ESMs outputs under different future climate scenarios (Dai, 2012; Naumann *et al.*, 2018; Spinoni *et al.*, 2020; Vicente-Serrano *et al.*, 2020a; Zhao and Dai, 2022). According to these scenarios, drought severity would increase, mainly as a consequence of the enhanced AED in a warming climate. Nonetheless, some studies suggest uncertainty of using these metrics (e.g. Berg and Sheffield, 2018; McColl *et al.*, 2022). Specifically, the criticisms argue are that these indices are not necessarily representative of the metrics based on water storage (i.e. soil moisture), surface water generation (i.e. runoff) or vegetation activity (i.e. leaf area and net primary production). These arguments would be supported by the notion that hydrological and ecological systems might show different dynamics and responses under future climates (Berg and Sheffield, 2018; Scheff, 2018). Furthermore, CMIP models generate simulations of hydrological and plant metrics, which would make it unnecessary to focus on climate metrics as proxies of drought impacts (McColl *et al.*, 2022). Moreover, drought indices that include AED in their calculations might overestimate drought severity under high=emissions future climate scenarios. This is simply because future increase in AED is likely to be higher than the expected increase in land evapotranspiration (Et) (Roderick *et al.*, 2015a; Milly and Dunne, 2016; Scheff, 2018; Yang *et al.*, 2019), which is also determined by water availability.

As such, assessments of drought projections based on different drought metrics make it necessary to provide a more complete spatio-temporal comparison of different drought metrics to provide a more robust picture of how drought responds to future climate. Nevertheless, although recent studies have analysed global drought projections based on the latest model outputs from the CMIP6 using different drought metrics (e.g. Cook *et al*., 2020; Ukkola*et al*., 2020; Li*et al*., 2021; Papalexiou*et al*., 2021; Zhu and Yang, 2021; Meng*et al*., 2022; Zeng*et al*., 2022; Zhao and Dai, 2022), few works assessed the robustness and coherence in the drought metrics under scenarios of high greenhouse gasses (GHG) emissions. Importantly, these studies lacked the opportunity to investigate some drought metrics that are essential for assessing agricultural and ecological droughts. As such, a focus on these gaps may provide new evidence that helps reconcile perspectives or stress uncertainties related to future trends in drought severity. On the other hand, it is necessary to test the robustness of the spatial and temporal consistency among the different drought metrics, which can give indications on the reliability of drought projections. In the pursuit of this background, the objectives of this study are to i) determine future drought projections based a more complete set of drought metrics to date, providing a more complete mosaic of current global studies and ii) determine the spatial and temporal coherence among the different drought metrics in replicating drought severity. Accordingly, the current global assessment can contribute to the arising debate on the robustness of the different drought metrics, providing new evidences on CMIP6 model uncertainties for agricultural, ecological, and hydrological drought projections under a high-emission climate scenario.

2. Data and Methods

We employed monthly data of a set of hydroclimatic variables from the CMIP6 experiment (Eyring *et al*., 2016). These variables included precipitation, runoff, total column soil moisture, leaf area index (LAI) and net primary production (NPP). Data were provided for the historical period (1850-2014) and for the Shared Socioeconomic Pathway (SSP; 5-8.5) from 2015 to 2100. All CMIP6 individuals that secure data for the necessary variables, as well as the period 1850-

2100, were considered in our analysis (see Supplementary Table 1). Recalling that the CMIP6 outputs are provided in different native spatial resolutions, we interpolated data to a common resolution of 2.5° x 2.5°. To assess future projections in drought severity, our decision was made to consider the SSP5-8.5 scenario, which represents the worst possible scenario compared to the historical experiment.

The standardised drought indices were computed based on the common data inputs (e.g. precipitation, runoff, total column soil moisture, LAI and NPP). Nonetheless, other indices were computed using a combination of new variables. For example, maximum and minimum air temperatures, relative humidity, wind speed and solar radiation, were used to calculate AED following the Penman-Monteith FAO-56 equation (Pereira *et al*., 2015). Overall, based on these data and data of Evapotranspiration (Et), we calculated different indices using: i) the difference between precipitation and AED (P-AED), which is a metric that has been widely used for drought assessment since it summarises the balance between the water available in the form of precipitation and the existing AED (Vicente-Serrano *et al.*, 2010; Tomas-Burguera *et al.*, 2020a), ii) precipitation minus land evapotranspiration (P-Et), which is considered a long-term water budget and has been accordingly used to assess drought severity in several works (e.g. Padrón *et al.*, 2020), and iii) the difference between Et and AED (Et-AED), which compares the difference between the available water to evaporate and the water demand by the atmosphere (Kim and Rhee, 2016; Vicente-Serrano *et al.*, 2018) and is highly related to plant water stress (Stephenson, 1990). All these drought metrics were transformed into the same standardised units to make robust spatial and temporal comparisons. To fit data distribution, a log-logistic distribution was used , which is capable of standardising different climate and hydrological records under different climate conditions, as being evidenced in earlier works (e.g. Vicente-Serrano and Beguería, 2016; Vicente-Serrano *et al*., 2020a). The only exception was for precipitation, which was fitted to a Gamma distribution (Stagge *et al.*, 2015b). We tested the goodness of fit of the standardized indices using the coefficient of determination

(R^2) of the QQ plots, which compare the empirical probability distribution function (pdf) of each index and the pdf of the standard normal distribution. Results demonstrate that R^2 were almost close to 1 for majority of the world regions (Fig S1), with small deviations among the models (Fig S2) and for specific timescales (e.g. 3-month and 12-month). Afterwards, a second standardisation procedure was carried out independently for each of the 12 monthly series of the indices. To make this standardisation, both the mean and the standard deviation were computed for the reference period 1850-2014. This procedure minimizes the possible impacts of strong trends presented in the analysed variables for future scenarios in the possibility of calculating the drought indices (Vicente-Serrano et al., 2020a). Furthermore, this standardisation allows for a robust spatial and temporal comparability between the different metrics. Accordingly, drought duration and magnitude can be quantified for each time series and for the different indices. Drought events were identified using the run theory (Tallaksen *et al.*, 1997; Fleig *et al.*, 2006), considering a threshold of z = -1.28, which corresponds to a 10% probability of a standard normal observation being below that value. For drought event identification, all indices were computed at the 3-month time scale. To analyse the trends in the duration and magnitude of drought events, a linear regression model was fitted as a function of time, and the estimated slope was used to quantify the amount of change over time. The significance of these changes was assessed using the Mann–Kendall test (Kendall, 1948; Mann, 1945).

We analysed the relationship between the annual indices (computed at 12-month time scale) using the Kendall´s rank correlation coefficient, i.e., Kendall's τcoefficient (Kendall, 1938). This coefficient is a nonparametric measure of rank correlation that is more suitable than parametric statistics (e.g. Pearson's linear correlation coefficient) because it accounts for the non-linear relationships between variables.

For each grid point, the temporal agreement between the indices (computed at 12-month scale) was assessed by obtaining the percentage of simultaneous occurrence of years in which a pair of indices were below z=-1.28, thus producing a 2-dimensional representation of the results. Also, we computed the percentage of grid points where each pair of indices showed z-value below -1.28, resulting in a time series.

3. Results

3.1. Evolution of drought severity based on different metrics

Fig. 1 shows the evolution of the world land surface affected by drought between 1850 and 2100. It is computed as the percentage of land grid points below the 5th percentile of each raw (non-standardised) variable. This percentile is computed independently for each month, considering the 1850-2014 reference period. For all the variables, we found an increase in the world land surface impacted by drought from 1850 to 2010, albeit with some considerable spatial differences. Results demonstrate that precipitation, leaf area, and runoff will likely show a small increase of drought severity in future - scenarios. For precipitation-Et and NPP, the increase was mostly intermediate, although a sharp increase in NPP is noted between 2010 and 2030, followed by a constant behaviour to the end of the twenty-first century. For precipitation-AED, Et-AED and soil moisture, a remarkable increase is noted at the end of the century. As illustrated in Figs S3 and S4, some variables exhibited important seasonal and regional differences. For example, during the boreal winter season, drought based on NPP, soil moisture, and Et-AED increased. Rather, for precipitation and runoff, irrelevant drought increase was noted from 1850 to 2100. On the contrary, in the boreal summer season, the main drought increase was recorded for precipitation-AED, Et-AED, and soil moisture, with little increase for other variables (e.g. precipitation, runoff, and precipitation-Et).

Overall, we noted an increase in the magnitude of drought events that affects large areas of the world in terms of precipitation-AED, Et-AED, and soil moisture, albeit with significant spatial differences (Fig. 2). Interestingly, these three drought metrics showed a high agreement in terms of the areas that are likely to exhibit the highest increase in the magnitude of drought periods, including the Mediterranean region, Central America, northern South America and western South America, West Africa and South Africa. Nevertheless, it can be noted that the areas affected are much larger using Et-AED metric, with almost the entire land showing an increase in drought severity. Meteorological droughts, based on precipitation, showed an increase in drought magnitude in areas of Central and South America, West Africa, South Australia and the Mediterranean region, although this increase is not as high as suggested by other drought indices (i.e. Et-AED, and soil moisture). This pattern was almost similar when considering precipitation-Et, although some areas of South America did not show an increase in drought severity, suggesting that –in specific regions- the increase in drought magnitude can be reduced if Et is included in the calculations. Drought magnitude trends based on runoff showed smaller changes than considering exclusively precipitation, demonstrating that CMIP6 models project a less increase in the magnitude of hydrological droughts than in the magnitude of meteorological (precipitation) droughts. LAI did not show an increase in the magnitude of drought events in large areas of the world, except for parts of East Brazil. Thus, the spatial pattern was sparse on the global scale, with strong regional variability and a dominance of no changes or decrease in the magnitude of drought events in some regions (e.g., South America, Southeast Asia, Central Europe, and North America). Notably, the NPP-based assessment showed a strong reinforcement of drought magnitude in the high latitudes of the Northern Hemisphere. Rather, in some areas of Africa, South America and Southeast Asia, a decrease in the magnitude of the drought episodes, based on the NPP, was noted. . Changes in the duration of drought events were almost similar to those of drought magnitude, particularly in terms of spatial patterns and the behaviour of the different drought metrics (Fig. S5).

Some drought metrics show high consistency in identifying positive trends in drought magnitude among the different models. Fig. 3 shows the percentage of models showing positive and statistically significant trends in drought magnitude between 1850 and 2100. As depicted, almost all models defined the same the regions with strong increase in drought magnitude considering precipitation-AED and Et-AED. This agreement was much lower for soil moisture, , even in large regions where the multimodel median values showed an increase in drought magnitude. A representative example is found in southern North America and South Africa, where multimodel medians showed a large increase in drought magnitude, while less than 40% of the models showed a positive and significant trend. In other regions wherea decline in drought magnitude was observed like northern South America or the Mediterranean, the percentage of models showing significant declining trends was roughly 50%, suggesting a strong uncertainty in model projections. Notably, although precipitation, precipitation-Et and runoff showed a drought increase in fewer regions than soil moisture, the consistency of this increase among models seems to be greater. More than 50% of the models suggested a positive and statistically significant increase in drought magnitude in northern South America and Central America, the Mediterranean and southern Africa for precipitation. A similar pattern was evident for vast areas in North and South America, Central Africa, and Central and South Asia when considering P-Et. This suggests that Et projections suppress the trend toward higher drought magnitudes in Southern Africa in comparison to precipitation-based projections, with only few models showing a positive and statistically significant trend. Interestingly, for runoff almost 50% of the models suggested a significant increase in drought magnitude in large regions of the Northern Hemisphere (e.g. Alaska, Labrador, Scandinavia, West Russia), while they did not witness a relevant increase in drought magnitude based on precipitation and precipitation-Et metrics. In the same context, apart from the high latitudes of the Northern Hemisphere, there were no regions where more than 30% of models showed an increase in drought magnitude for the NPP. Interestingly, results demonstrate that drought magnitude based on LAI will not change anywhere worldwide, with almost no model suggests significant changes.

Like drought magnitude, similar patterns of drought duration changes were observed globally (Fig. S6), with majority of the models suggesting no significant changes in ecological and agricultural droughts across majority of the world regions under scenarios of high greenhouse gas emissions.

The negative trends in drought magnitude (Fig. 4) and duration (Fig. S7) indicated few regions and metrics in which the models agree on a decrease in drought severity, mainly for precipitation in the high latitudes of the Northern Hemisphere. Even for LAI and NPP, the percentage of models that showed a decrease in drought magnitude is low. As depicted, although some areas, based on some metrics, showed a projected decrease in drought duration and magnitude with multimodel medians (e.g. Southeast Asia with LAI, Central Africa with the NPP, West Russia with soil moisture), there is still large inconsistency among the models. In the same context, while a steady increase in drought duration and magnitude was projected for some regions and variables, only few areas witnessed a decrease in drought duration and magnitude, irrespective of drought metric used. Thus, although there are important uncertainties between drought metrics and models related to the increase of drought duration and magnitude, there is a high consistency between models and metrics concerning drought decrease since drought magnitude and duration are not expected to decrease much under a scenario of high greenhouse gasses emissions.

3.2. Spatio-temporal relationships among drought metrics

In addition to knowing the consistency of trends between different drought metrics and models, it is also relevant to analyse the consistency of the temporal relationship in the drought severity based on these metrics (Fig. S8). As illustrated, we found strong annual relationships between some pairs of drought indices in the historical period. For example, the correlation was higher than 0.8 between precipitation and precipitation-AED and between precipitation and precipitation-Et in most areas of the world. Also, a high correlation was observed between precipitation-AED and precipitation-Et, with few exceptions, mainly in arid and semiarid regions where correlations decreased. Other pairs of drought metrics showed lower relationships on global scale, with important spatial differences. For example, the relationship between precipitation and Et-AED was only high in water-limited regions, where Et is mostly determined by water availability. It is worth mentioning that the relationship between precipitation (and also between the other climatic metrics) and soil moisture was low in most regions. Thus, the correlation with soil moisture was higher considering precipitation-AED and particularly Et-AED in regions like South America, Africa, and South Asia. LAI and NPP showed high correlations particularly in water-limited and cold regions. Nevertheless, these two ecological variables showed low correlations with the different meteorological drought metrics, suggesting that the interannual variability of agricultural and ecological droughts simulated by models is independent from those of climatic droughts in most regions of the world. This pattern was also observed considering soil moisture, with low correlations found between the interannual variability of soil moisture and the NPP and LAI in most regions, irrespective of biome types and bioclimatic conditions. The relationship between precipitation and runoff was high in most regions of the world, except for North America and most of Eurasia. In contrast, the relationship between interannual variability of runoff and soil moisture tended to be low globally, apart from the Mediterranean, northern South America, and Africa. Similarly, ecological metrics (i.e. NPP and LAI) showed low correlations with runoff worldwide.

Overall, these results suggest that, except for the high relationship between different climate metrics and their corresponding spatial differences that are mainly determined by the average water availability and temperature, the temporal relationship between different drought metrics was generally low in most regions of the world. This relationship was particularly low between climatic and vegetation metrics, as well as between soil moisture and other drought metrics.

The spatial pattern and the magnitude of the temporal relationships between the different variables did not show important changes considering future simulations (2015-2100), as compared with historical simulations (Fig. S9), albeit with some important exceptions (Fig. 5). For example, the relationship between the interannual variability of precipitation and other climatic drought metrics generally decreased, which is quite relevant in some areas of Central Asia considering precipitation-AED, but also in the Sahel and high latitudes of the Northern Hemisphere considering Et-AED. On the contrary, the relationship between precipitation and precipitation-Et remained stable for both the historical period and future. Also, we found a decrease in the relationship between precipitation-AED and precipitation-Et in some regions of Europe, South America, and Africa. The relationship between LAI and NPP was stable for the historical period and future simulations in most regions, albeit with a trend to reinforce in some regions. In addition, the relationship between precipitation and LAI tended to reinforce in the high latitudes of the Northern Hemisphere. This was also observed with the NPP, although a decline in the correlation between precipitation and NPP was observed in the Mediterranean, southern North America and northern South America. While the relationship between NPP and precipitation-AED was low during the historical period, this relationship was projected to decline further in the future, particularly in arid regions, the Amazon basin, and some wet areas of Africa. The decrease in the relationship with the NPP was even more severe when considering Et-AED, with an overall global decline. In addition, the relationship between NPP and soil moisture is likely to decline over large areas (e.g. the Mediterranean, northern South America, southern Africa, and Australia). Finally, the relationship of the runoff to other drought metrics tended to be stable between the historical period and the future high emission scenario, although a decreasing correlation with precipitation was observed in Scandinavia, and particularly with precipitation-AED and Et-AED in most Africa and the Amazon basin.

The temporal agreement in drought conditions among the different metrics is small in most regions during the historical period (Fig S10), suggesting that the annual drought conditions tend to differ noticeably between metrics. There was some agreement in the identified drought periods between precipitation and precipitation-AED, except in arid lands. A similar pattern was also noted between precipitation and precipitation-Et in wet regions and between precipitation-AED and Et-AED in arid lands. Nevertheless, the agreement in the occurrence of droughts between climatic, ecologic, and hydrologic metrics was small. Herein, it is worth to note that while our analysis is restricted to annual droughts to reduce the role of seasonality and the lags in the response of hydrological, agricultural and ecological drought conditions to meteorological droughts and irrespective of the physical consistency among models, drought periods mostly do not coincide in time among the different metrics. For the projected scenario, the temporal agreement between metrics shows some increase (Fig. S11). This is particularly relevant in some regions, such as the Mediterranean region, southern Africa, the Amazon basin, and Central America when comparing drought episodes recorded with precipitation and precipitation-AED, precipitation-Et, Et-AED and soil moisture and also between precipitation-AED and precipitation-Et and between Et-AED and soil moisture, particularly in water-limited regions. The agreement in the temporal identification of drought conditions also increases when comparing the climatic indices and the runoff in some areas, particularly in the Amazon and the humid regions of Africa, suggesting an agreement in annual droughts between some pairs of drought metrics, especially in water-limited or humid regions (Fig. 6).

The temporal agreement between annual droughts was low during the historical period between the different metrics, and also with low spatial agreement, suggesting that the global spatial patterns of annual drought severity usually did not agree between drought metrics (Fig. 7). The spatial agreement of drought conditions tends to increase under future climate change, in particular for some metrics (e.g. precipitation-AED and precipitation-Et, precipitation-AED and Et-AED, precipitation-AED and soil moisture). Nevertheless, the spatial agreement between droughts on the annual scale between climatic indices, runoff, and ecological droughts was low in both the historical experiment and the projected scenario, indicating spatial inconsistency in replicating annual droughts among the different drought metrics obtained from ESMs.

4. Discussion

This study analysed long-term evolution of different drought metrics on a global scale using CMIP6 models from 1850 to 2100. These metrics represent different climatic, hydrologic, and ecological variables. Results were presented for the historical experiment (1850-2014) and future projections (2015-2100) under a high-emission scenario (SSP5-8.5). While numerous studies assessed drought severity for future climate using CMIP6 models (e.g. Cook *et al*., 2020; Ukkola*et al*., 2020; Papalexiou*et al*., 2021; Wang*et al*., 2021; Guo*et al*., 2022; Zhao and Dai, 2022), our assessment employed a larger number of drought metrics, including climate-based (precipitation, precipitation-AED, precipitation-Et, Et-AED), hydrological-based (soil moisture and runoff) and plant physiology-based metrics (LAI and NPP). An evaluation of this variety of different metrics is essential to assess different drought types (meteorological, agricultural/ecological and hydrological) and to determine their consistency in terms of projected drought severity. Our results, as suggested by most models and drought metrics, suggest that drought would increase in southern North America, Central America, the Amazon region, the Mediterranean, southern Africa, and southern Australia, which agrees with earlier studies (e.g. Cook *et al*., 2020; Ukkola*et al*., 2020; Seneviratne*et al*., 2021; Wang*et al*., 2021; Zhao and Dai, 2022). Also, in accordance with previous studies (Cook *et al.*, 2020; Scheff *et al.*, 2021), our results showed important differences in drought projections as a function of drought metrics. For example, the use of AED-based drought metrics(e.g. the Standardised Precipitation Evapotranspiration Index (SPEI)) revealed that drought severity is likely to enhanced in future , as compared to those metrics based on precipitation, precipitation-Et, and runoff. This finding agrees with some investigations based on CMIP6 (e.g. Zeng *et al.*, 2022), and CMIP5 outputs (e.g. Cook *et al.*, 2014) and also by studies that employed other metrics like the Palmer Drought Severity Index (PDSI) (e.g. Scheff *et al.*, 2021; Yang *et al.*, 2021; Zhao and Dai, 2022). The different magnitude of drought as simulated based on hydrological (i.e. runoff) and climatic drought indices (which use AED in the calculations) is behind the overestimation of drought severity based on climatic indices under high emissions climate change scenarios as suggested by some studies(Berg and Sheffield, 2018; Scheff, 2018; Greve *et al.*, 2019; Berg and McColl, 2021).

While it can be argued that focusing on the metrics directly indicative of impacts in agricultural, ecological and hydrological systems (i.e. soil moisture, runoff, net primary production, and leaf area index) instead of climatic proxies of drought severity can be a more practical approach (McColl *et al*., 2022), we believe that models can show uncertainties in simulating complex hydrological and plant physiology processes. In addition, hydrological and ecological outputs from CMIP models could be affected by more uncertainty in comparison to climatic metrics that can be simulated easier, irrespective of any possible coupling mechanisms. For example, the spatial and temporal variability in soil moisture involves several processes, some of them are unknown, while others are difficult to simulate (van den Hurk *et al.*, 2011; Lu *et al.*, 2019). This may explain poor agreement between soil moisture observations and model simulations (Yuan and Quiring, 2017; Ford and Quiring, 2019). Streamflow generation is also very complex and models usually fail to simulate hydrological droughts (Tallaksen and Stahl, 2014; Barella-Ortiz and Quintana-Seguí, 2018). Plant physiology is also a key factor controlling both hydrological, agricultural and ecological droughts, and models show strong limitations and uncertainties in simulating plant physiological processes and water interchanges with soil and atmosphere (Liu *et al.*, 2020). These problems are even more important for future climate projections (Gentine *et al.*, 2019), given that other processes may introduce other sources of uncertainty (e.g. the role of atmospheric CO_2 concentrations) (De Kauwe *et al.*, 2021). Therefore, although some studies argue that plant and hydrological drought metrics obtained from model simulations can probably be more accurate than AED-based climatic indices, we believe that these metrics may also be affected by several strong uncertainties.

One of the novelties of our study is the use of diverse metrics, which is fundamental to address drought characteristics and impacts. In particular, we employed the Standardised Evapotranspiration Deficit Index (SEDI), based on the difference between Et and AED, which is informative on plant water stress (Kim and Rhee, 2016; Vicente-Serrano *et al.*, 2018; Li *et al.*, 2019, 2020; Zhang *et al.*, 2019; Alsafadi *et al.*, 2022; Jiang *et al.*, 2022) with several biogeographic implications (Stephenson, 1990). Changes in the SEDI, both in spatial patterns and drought severity, were almost similar, or even stronger than those obtained by the SPEI, and are characterised by an increase in drought severity under future scenarios of high anthropogenic emissions. In addition, we used two eco-physiological metrics, LAI and NPP, which have been considered by few studies as metrics of drought severity in model simulations(e.g. Scheff et al., 2021). As opposed to the SEDI, our assessment based on the LAI and NPP did not suggest an increase in agricultural and ecological drought severity, except for the high latitudes of the Northern Hemisphere. This may be explained by the role of snow and permafrost melt processes that could affect water availability (Chen *et al.*, 2021).

The picture provided by our eight drought metrics showed some paradoxical projections that are difficult to explain by coherent hydrological and plant physiological processes. In particular, different studies focusing on plant physiology have highlighted that plant mortality will strongly increase in future as a consequence of increased plant water stress and air temperature (e.g. Williams *et al*., 2013; McDowell and Allen, 2015; Xu*et al*., 2019; Brodribb*et al*., 2020). This assessment is consistent with observations of ecological and agricultural impacts of droughts, which are clearly reinforced by the observed increase in AED (Breshears *et al.*, 2005, 2013; Allen *et al.*, 2010; Carnicer *et al.*, 2011; Lobell *et al.*, 2011; Asseng *et al.*, 2015; Sánchez-Salguero *et al.*, 2017). Nevertheless, in opposition to this empirical evidence and the strong increase of drought severity as suggested by some climatic indices, LAI-based drought projections suggested that –in few cases where precipitation is projected to increase(e.g. Central America, southwestern Australia and the south of the Amazon region), drought severity is likely to increase in future simulations.

The limited increase in drought severity based on ecological metrics is difficult to be supported according to the widely known response of plants to water availability (Vicente-Serrano *et al*., 2020b) and atmospheric water demand (Breshears *et al.*, 2013; Grossiord *et al.*, 2020), particularly in water-limited regions where meteorological droughts (e.g. southern Africa, southern North America, and the Mediterranean), and AED are projected to increase (Scheff and Frierson, 2015; Vicente-Serra*no et al*., 2020d). These conditions can lead to a remarkable increase in plant water stress incompatible with increases in LAI and NPP. Thus, the only way to avoid changes in ecological droughts in water-limited regions, where climate aridity is projected to increase, is probably related to the physiological effects of the atmospheric CO_2 concentrations (Mankin *et al.*, 2017; Gonsamo *et al.*, 2021; Scheff *et al.*, 2022). Several studies have showed a reduction in the leaf stomatal conductance and plant resistance to water stress in response to enhanced atmospheric CO_2 concentrations (e.g., Ceulemans and Mousseau, 1994; Ainsworth and Long, 2005; Donohue *et al.*, 2013; Green *et al.*, 2020). However, the effects of increasing CO_2concentrations on ecological and agricultural drought severity are very complex (Allen *et al.*, 2015; De Kauwe *et al.*, 2021), and there are still several uncertainties in the assessment of these effects based on ESMs (Gentine *et al.*, 2019; De Kauwe *et al.*, 2021), tended to overestimate the effects of increasing CO_2 concentrations on plant physiology (Kolby Smith *et al.*, 2015; Marchand *et al.*, 2020; Zhao *et al.*, 2020). Moreover, CO_2 effects would not ameliorate plant stress during periods of water deficit, given that leaf stomatal conductance would not be controlled by CO_2 concentrations, but mostly by soil moisture content (Morgan *et al.*, 2004; Xu *et al.*, 2016; Menezes-Silva *et al.*, 2019). Therefore, our assessment of future agricultural and ecological droughts based on model simulations is highly uncertain given the current evidence of the responses of plants to enhanced water stress and AED and the several sources of uncertainty in the modelling of the carbon cycle by the ESMs (Padrón *et al.*, 2022). Thus, it is difficult to argue that ecological droughts will not increase in areas in which models suggest a strong decrease in precipitation and a remarkable increase in AED.

For hydrological drought projections, our study indicates that future projections of droughts quantified with soil moisture tend to resemble the pattern of the projections of drought severity using SPEI. This seems to disagree with some previous studies that had suggested less increase in soil moisture deficits than the decrease in meteorological indices including AED in future drought projections (Milly and Dunne, 2016; Berg and Sheffield, 2018). This disagreement can basically explained by the different statistical methods used to assess future projections. These models are strongly affected by the autocorrelation of the drought metrics, as well as by focusing on changes in the average values versus the tails of the complete set of the distribution values (Vicente-Serrano *et al.*, 2020a). Thus, the last IPCC report has showed a strong increase in drought severity worldwide based on extreme events of the total column soil moisture, particularly during the boreal summer season (Seneviratne *et al.*, 2021). This increase in the duration and magnitude of soil moisture deficits would be coherent with an increase in agricultural and ecological drought severity, even more considering the strong increase in AED, as projected by the CMIP models (Scheff and Frierson, 2015; Vicente-Serrano *et al*., 2020d), which would cause enhanced plant stress. Also, uncertainties in the projected Et are noticeably affect drought projections based on precipitation-Et, which is usually considered a metric of water availability. Thus, it is curious that the projections of meteorological droughts based on precipitation showed a stronger increase in drought duration and magnitude than projections based on precipitation-Et and runoff. It would be expected that hydrological droughts will not increase at similar rates of agricultural and ecological droughts, in response to increased AED. This is basically because the response of streamflow to enhanced AED is expected to be lower than to precipitation, as observed with streamflow data (Ficklin *et al.*, 2018; Yang *et al.*, 2018; Vicente-Serrano *et al.*, 2019). This issue has been well-established based on the ESMs, as runoff simulations mostly respond to precipitation at short time scales (Scheff *et al.*, 2022). However, even responding more to precipitation than to AED, it is difficult to support a smaller increase in drought severity by runoff than by precipitation under scenarios of a high increase in AED. This behaviour would be mostly explained by the suppression of Et as a consequence of the decreased leaf stomatal conductance given the enhanced atmospheric CO_2concentrations, which would reduce the severity of hydrological droughts (Roderick *et al.*, 2015b; Milly and Dunne, 2016; Yang *et al.*, 2019). However, a main constrain of this assessment is that the influence of this mechanism on future Et is highly uncertain in ESMs (Vicente-Serrano *et al*., 2022a). Moreover, Et is also observed to increase during dry periods (Zha*o et al*., 2022) and evaporation in surface water bodies is expected to increase in future scenarios (Wang *et al.*, 2018). For these reasons, it is difficult to argue that hydrological droughts quantified using precipitation-Et and runoff will increase less than meteorological droughts, based on precipitation, in future scenarios.

In addition to the comparative assessment of drought trends based on different drought metrics, another aspect of novelty in our study is that it assesses the spatial and temporal relationship between different drought metrics under the historical experiment and future SSP5-8.5 scenario. Specifically, we found that the temporal relationship between the precipitation-based climatic metrics (i.e. precipitation, precipitation-AED, and P-Et) is high worldwide, with some spatial exceptions (e.g. in water-limited regions for P-Et). This behaviour is expected given that precipitation is a main controller of the interannual variability of drought conditions(Vicente-Serrano *et al.*, 2015; Tomas-Burguera *et al.*, 2020b). For example, in the case of SPEI, precipitation explains more than 90% of the variability of this index, while AED is only relevant during periods of precipitation deficit, particularly in water-limited regions

(Tomas-Burguera *et al*., 2020b). This main role of precipitation is also observed in other drought indices such as the PDSI (van der Schrier *et al.*, 2013; Vicente-Serrano *et al.*, 2015). On the other hand, under the SSP5-8.5 scenario, the correlation between precipitation and AED-based drought indices is expected to decrease, suggesting a greater role of AED. Nevertheless, this temporal relationship remains high in most world regions.

The close relationship found between climate drought indices in historical and future simulations contrasts with the low correlations found between climatic and ecological drought indices, given the low percentage of years when drought conditions coincide following meteorological and ecological metrics. The interannual variability of LAI and NPP showed high agreement in both the historical period and in the future scenario. This is in agreement with observations recorded in the last decades using vegetation activity from satellites (as a surrogate of the leaf area) and tree-ring growth (as a surrogate of NPP) (Vicente-Serrano *et al*., 2016, 2020c). Nevertheless, unexpectedly, we noted a poor relationship between the temporal evolution of both LAI and NPP and the climatic drought indices, albeit with the use of a wide set of metrics used here that highly represent plant water stress conditions (e.g. Et-AED). Moreover, this low relationship is also found between the ecological variables and soil moisture, which is one of the main factors controlling vegetation activity and carbon uptake worldwide (Green *et al.*, 2019). This low relationship between climatic indices (and soil moisture) and ecological metrics could be explained by the uncoupling between water availability and plant water requirements as a consequence of the physiological effects of atmospheric CO_2 concentrations (as discussed above). Nevertheless, low interannual correlations were also found in the historical experiment. We consider that the low relationship between ecological drought metrics and climatic and soil moisture metrics introduces another important source of uncertainty in the assessment of the drought severity under future climate scenarios. It is expected that the agreement between NPP, LAI, and the different climatic metrics and soil moisture should be high, given the climate forcings used in the historical experiment. Thus, based on different vegetation metrics, numerous studies found strong temporal correlations between climate drought indices and soil moisture and different ecological measurements in the past decades, including satellite metrics (e.g. Vicente-Serrano *et al.*, 2013; Bachmair *et al.*, 2018), and tree ring growth (e.g. Orwig and Abrams, 1997; Vicente-Serrano *et al.*, 2014). This unexpectedly low correlation between climatic droughts, soil moisture deficits and agricultural and ecological droughts during the historical experiment suggests that the temporal decoupling between these metrics is not related to the possible physiological effects of the enhanced CO_2 concentrations. Rather, it can probably be due to the existing limitations of the models in reproducing the real physiological response of vegetation to drought. In addition to the low temporal concordance, there is a general spatial disconnection between the occurrence of climatic and ecological droughts in different regions worldwide.

The temporal agreement between climatic drought metrics, soil moisture, precipitation-Et, and runoff is also low, both in the historical experiment and the SSP5-8.5 scenario. With the exception of the tropical and subtropical regions in the case of runoff, the remaining world showed low correlations with climatic metrics. Thus, the temporal correlations were low between the interannual variability of soil moisture and runoff in most regions of the world. This suggests that, considering climatic and hydrological drought metrics, the consistency of ESMs simulations on long temporal scales (i.e. annual) may be also affected by uncertainties. Thus, as opposed to CMIP6 outputs, the interannual variability of observed soil moisture and streamflow is highly consistent with climate variables in most basins of the world (Dai, 2021).

5. Conclusions

This study provided new evidence on the interannual relationships and long-term trends between drought types based on different drought metrics obtained from ESM simulations. The main conclusion is that the coherence of the trends and the interannual relationships between drought metrics show important uncertainties that can largely impact any robust assessment of drought projections under scenarios of enhanced emissions of greenhouse gases. Although some previous studies have suggested that the use of climatic drought indices could overestimate drought severity under future scenarios, this study indicates that projections based on hydrological (i.e. soil moisture and runoff) and ecological drought metrics (i.e. NPP and LAI) can introduce uncertainties and inconsistencies, particularly for the projected interannual relationship between drought metrics, as well as expected drought impacts under scenarios of high emissions of greenhouse gases and strong temperature increase. Still, there are several sources of uncertainty, particularly linked to the plant processes and the physiological influences of the enhanced CO_2 atmospheric concentrations, which have important implications for the assessment of both ecological and hydrological droughts in future scenarios. Recent evidence highlights increased drought effects on crop systems and natural environments in response to drought events characterised by warmer conditions (Breshears *et al.*, 2013; Williams *et al.*, 2013; Fontes *et al.*, 2018), but also hydrological implications given enhanced evaporation from crops, natural vegetation, and water bodies (Vicente-Serrano *et al.*, 2017; Friedrich *et al.*, 2018; Althoff *et al.*, 2020). Although the response of plant physiology and hydrological processes could change in the future, with more adaptive strategies to much warmer conditions leading to a reduction in the severity of hydrological, agricultural, and ecological droughts compared to climatic droughts conditions, these scenarios may be uncertain. Therefore, the same (or even greater) criticism could be made of the drought severity projections based on climatic drought indices using plant and ecological metrics, as these metrics do not seem to respond coherently in time and space to the occurrence of meteorological droughts and seem to underestimate the strong role of warming processes, already evident in some hydrological systems, but mostly in agricultural and ecological ones.

Drought severity projections are an extremely relevant topic with several environmental and socioeconomic implications, which deserves some scientific debate. Nevertheless, several studies based on models can present considerable uncertainties. Indeed, improving the knowledge and modelling of the complex processes involved could reduce these uncertainties, but we are probably still far from finding this solution. A focus on simple, but robust models, as suggested by McColl *et al.*(2022), could be a better approach to improve the assessment of future drought severity. However, this robust assessment may actually be simpler, as in future periods of precipitation deficits (anthropogenic or naturally=induced), the projected increased warming will cause more stress on hydrological and environmental systems as observed in near-present climate, irrespective of the projected trends in precipitation.

Data Availability Statement

The data from the CMIP6 models is available at the World Climate Research Programme (WCRP, https://esgf-node.llnl.gov/search/cmip6/).

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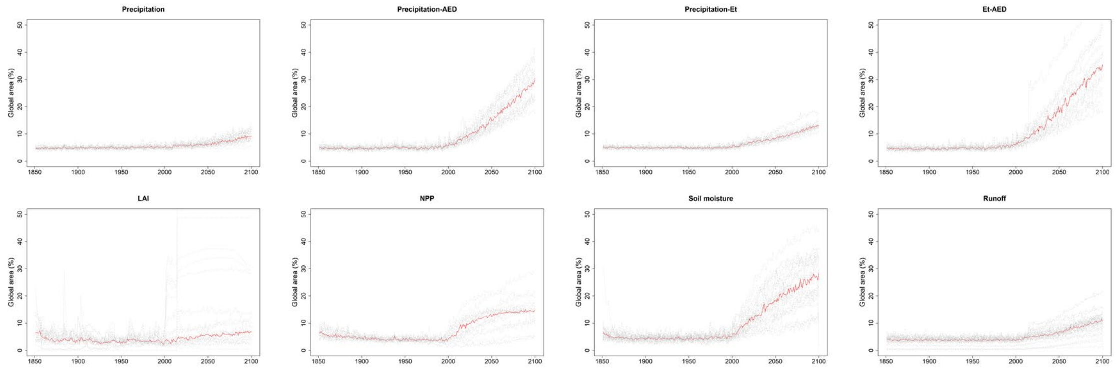

Fig. 1. Evolution of the annual average percentage of global land area affected by extreme dry conditions (5%) from 1850 to 2100. Grey lines represent the value for the different independent models and red lines refer to the median.

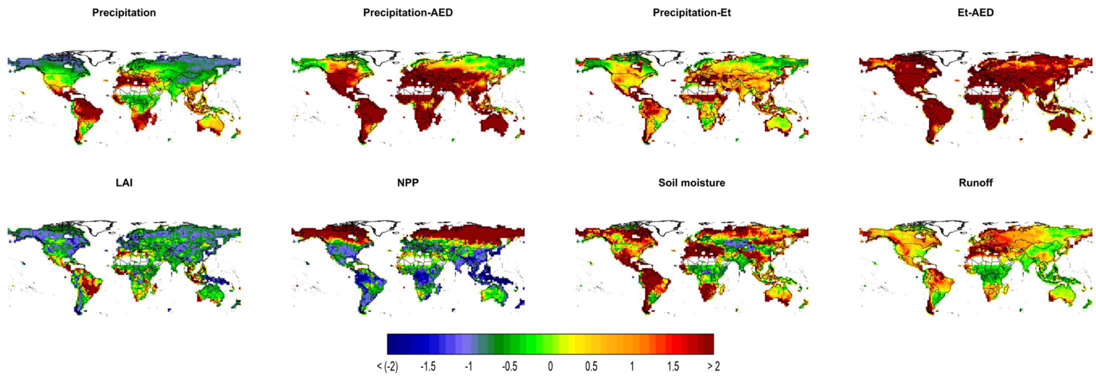

Fig. 2. Spatial distribution of the median trend in the magnitude of drought events between 1850 and 2100 (Factor: 100)

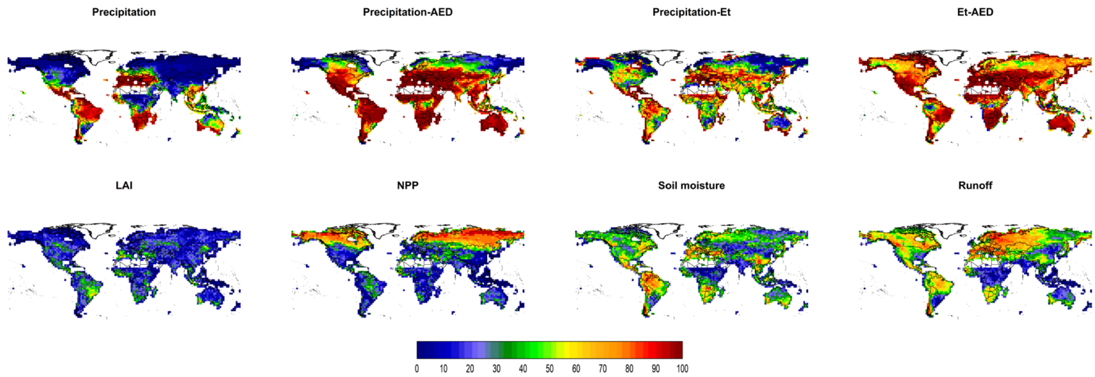

Fig. 3. Percentage of models showing positive and statistically significant trends in drought magnitude from 1850 to 2100

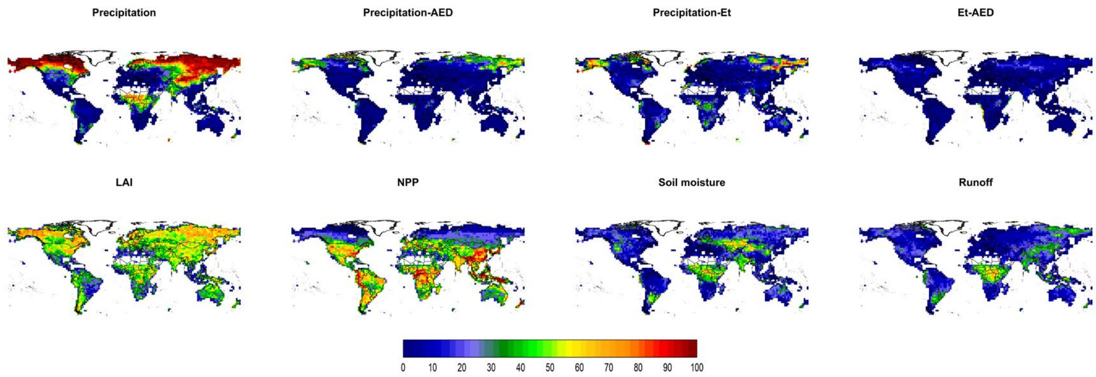

Fig. 4. Percentage of models showing negative and statistically significant trends in drought magnitude from 1850 to 2100

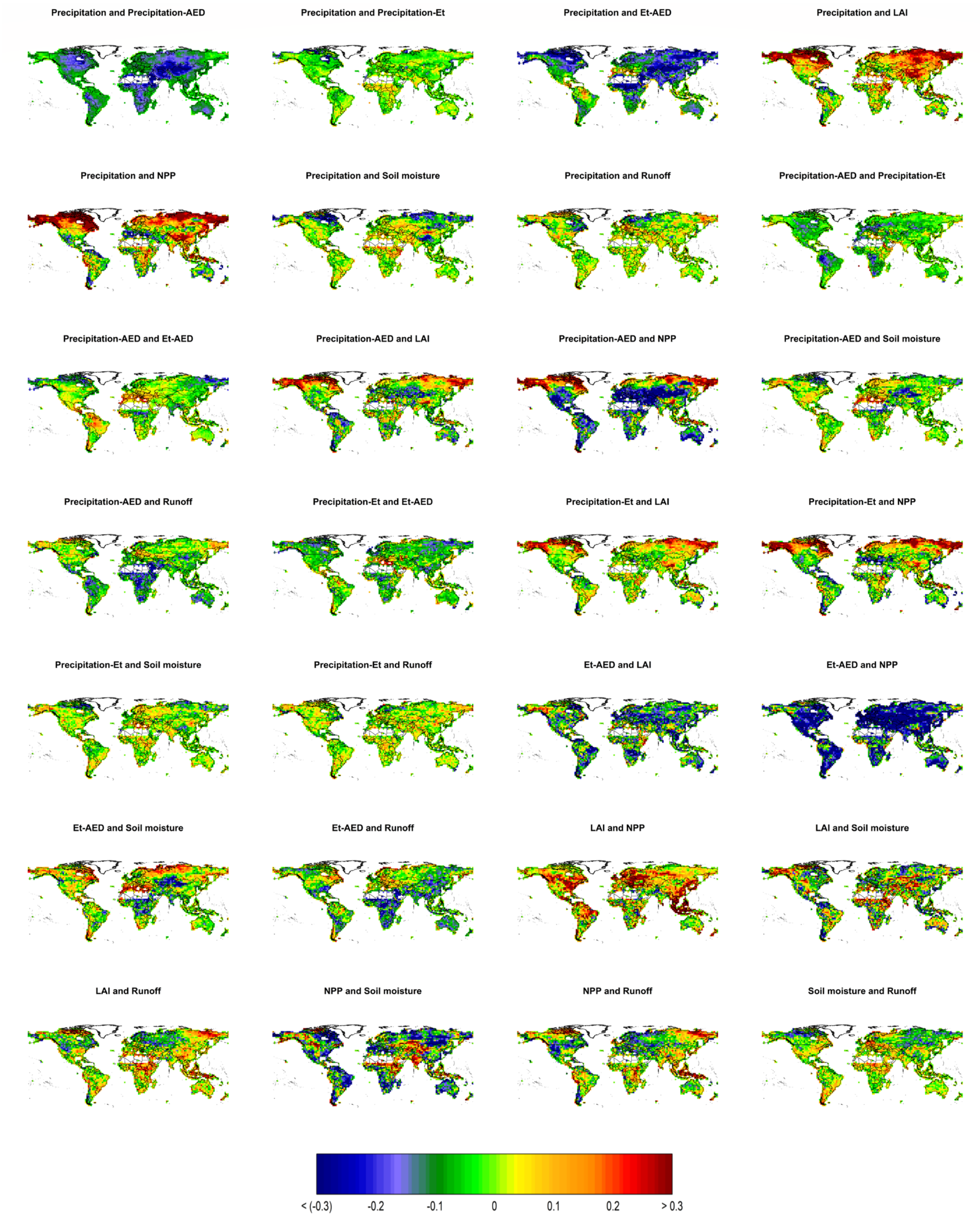

Fig. 5: Differences in the median Kendall's τ correlations between the projected (2015-2100) and historical period (1850-2014) for the different models

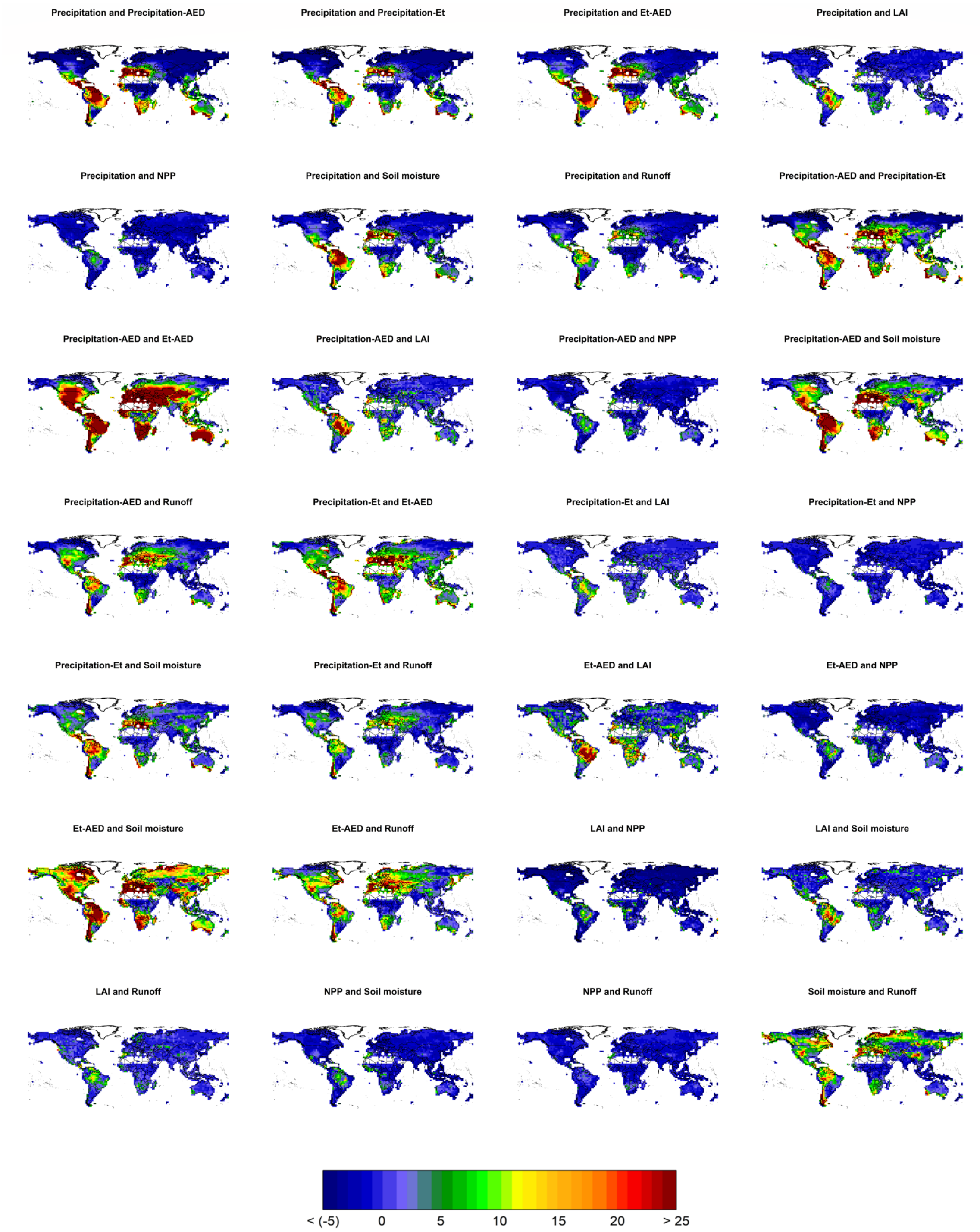

Fig. 6: Differences in the average percentage of temporal agreement among the different metrics between the projected (2015-2100) and the historical period (1850-2014) for the different models

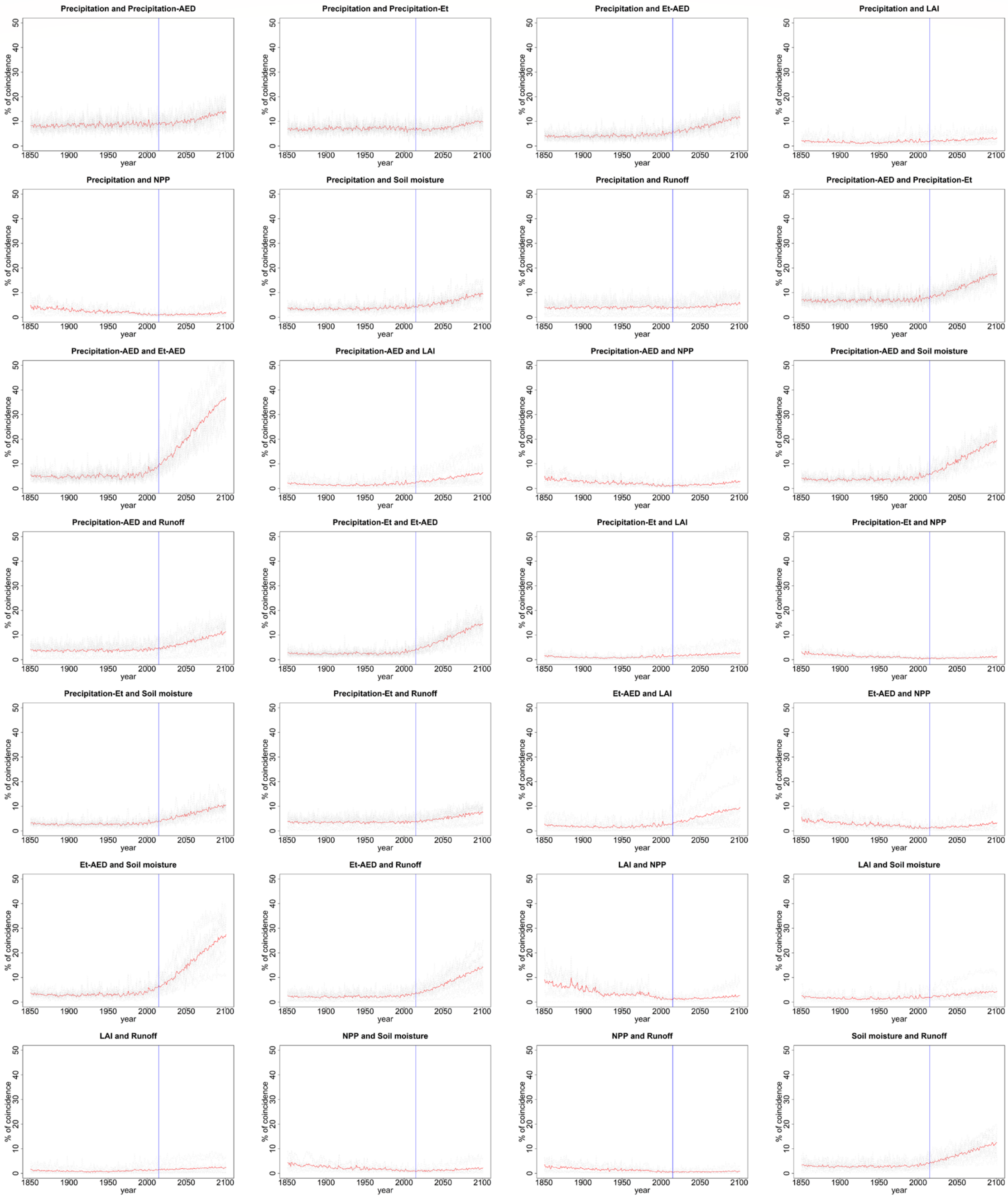

Fig. 7: Evolution of the spatial agreement of dry conditions between the different drought metrics.

Assessment of the global coherence of different types of droughts in model simulations under a high anthropogenic emission scenario

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Abstract

This study provides a global analysis of drought metrics obtained from several climatic, hydrologic and ecological variables in a climate change framework using CMIP6 model data. A comprehensive analysis of the evolution of drought severity on a global scale is carried out for the historical experiment (1850-2014) and for future simulations under a high emissions scenario (SSP5-8.5). This study focuses on assessing trends in the magnitude and duration of drought events according to different standardised indices over the world land-surface area. The spatial and temporal agreement between the different drought indices on a global scale was also evaluated. Overall, there is a fairly large consensus among models and drought metrics in pointing to drought increase in southern North America, Central America, the Amazon region, the Mediterranean, southern Africa and southern Australia. Our results show important spatial differences in drought projections, which are highly dependent on the drought metric employed. While a strong relationship between climatic indices was evident, climatic and ecological drought metrics showed less dependency over both space and time. Importantly, our study demonstrates uncertainties in future projections of drought trends and their interannual variability, stressing the importance of coherent hydrological and plant physiological patterns when analysing CMIP6 model simulations of droughts under a warming climate scenario.

Keywords: Climate change, drought projections, CMIP6 simulations, model uncertainty.

1. Introduction

Assessment of future drought projections is at the forefront of scientific debate in the current research on climate, hydrology, agriculture, and ecology. This is simply due to the multiple dimensions of droughts, which cause strong complexity for drought assessment and quantification (Lloyd-Hughes, 2014; Douville *et al*., 2021). In addition, the strong environmental and socioeconomic implications of drought changes in future climate scenarios adds more complexity to this debate (Van Loon *et al.*, 2016; Xu *et al.*, 2019; Naumann *et al.*, 2021).

In order to robustly assess future changes in drought severity, we must refer to different types of drought. This is fundamental to properly evaluate the impacts associated with drought in future climates. Generally, the concepts of meteorological drought (precipitation deficits), agricultural droughts(crop failure or yield decrease), ecological droughts (damages in natural vegetation, reduced photosynthesis activity, and carbon uptake and increased plant mortality), and hydrological droughts (reductions in the availability of water in different sources such as reservoir storages, streamflow and groundwater) are used commonly to refer to drought types. These types are largely impacted by different processes and physical and ecological implications (Wilhite and Buchanan-Smith, 2005; Lobell, 2014; Vicente-Serrano *et al*, 2020b; Douville *et al*, 2021).

In the literature, a wide spectrum of studies characterised drought projections on the global scale using model simulations of various climatic, hydrological, and vegetation variables under different future climates scenarios (e.g. Cook *et al*., 2014, 2020; Martin, 2018; Lu*et al*., 2019; Ukkola*et al*., 2020; Vicente-Serrano*et al*., 2020a; Zhu and Yang, 2021; Papalexiou*et al*., 2021; Zhao and Dai, 2021; Ridder*et al*., 2022; Zeng*et al*., 2022). Nonetheless, most of these studies focused on metrics directly simulated by different Coupled Model Intercomparison Projects (CMIP) since they allow to directly evaluate drought impacts on a variety of agricultural, ecological, and hydrological systems (Quiring and Papakryiakou, 2003; Hlavinka *et al.*, 2009;

Vicente-Serrano *et al.*, 2012; Stagge *et al.*, 2015a; Bachmair *et al.*, 2016, 2018; O'Connor *et al.*, 2022).

In the literature, the most widely used drought metrics for drought monitoring and impact assessment are synthetic indices that combine precipitation and atmospheric evaporative demand (AED), allowing for a direct quantification of drought severity and drought extent (Vicente-Serrano *et al.*, 2010; van der Schrier *et al.*, 2013; Tomas-Burguera *et al.*, 2020a; Dai, 2021), as well as their impacts on ecosystems (Bachmair *et al.*, 2015). For future simulations, different studies analysed drought projections based on these indices, employing ESMs outputs under different future climate scenarios (Dai, 2012; Naumann *et al.*, 2018; Spinoni *et al.*, 2020; Vicente-Serrano *et al.*, 2020a; Zhao and Dai, 2022). According to these scenarios, drought severity would increase, mainly as a consequence of the enhanced AED in a warming climate. Nonetheless, some studies suggest uncertainty of using these metrics (e.g. Berg and Sheffield, 2018; McColl *et al.*, 2022). Specifically, the criticisms argue are that these indices are not necessarily representative of the metrics based on water storage (i.e. soil moisture), surface water generation (i.e. runoff) or vegetation activity (i.e. leaf area and net primary production). These arguments would be supported by the notion that hydrological and ecological systems might show different dynamics and responses under future climates (Berg and Sheffield, 2018; Scheff, 2018). Furthermore, CMIP models generate simulations of hydrological and plant metrics, which would make it unnecessary to focus on climate metrics as proxies of drought impacts (McColl *et al.*, 2022). Moreover, drought indices that include AED in their calculations might overestimate drought severity under high=emissions future climate scenarios. This is simply because future increase in AED is likely to be higher than the expected increase in land evapotranspiration (Et) (Roderick *et al.*, 2015a; Milly and Dunne, 2016; Scheff, 2018; Yang *et al.*, 2019), which is also determined by water availability.

As such, assessments of drought projections based on different drought metrics make it necessary to provide a more complete spatio-temporal comparison of different drought metrics to provide a more robust picture of how drought responds to future climate. Nevertheless, although recent studies have analysed global drought projections based on the latest model outputs from the CMIP6 using different drought metrics (e.g. Cook *et al*., 2020; Ukkola*et al*., 2020; Li*et al*., 2021; Papalexiou*et al*., 2021; Zhu and Yang, 2021; Meng*et al*., 2022; Zeng*et al*., 2022; Zhao and Dai, 2022), few works assessed the robustness and coherence in the drought metrics under scenarios of high greenhouse gasses (GHG) emissions. Importantly, these studies lacked the opportunity to investigate some drought metrics that are essential for assessing agricultural and ecological droughts. As such, a focus on these gaps may provide new evidence that helps reconcile perspectives or stress uncertainties related to future trends in drought severity. On the other hand, it is necessary to test the robustness of the spatial and temporal consistency among the different drought metrics, which can give indications on the reliability of drought projections. In the pursuit of this background, the objectives of this study are to i) determine future drought projections based a more complete set of drought metrics to date, providing a more complete mosaic of current global studies and ii) determine the spatial and temporal coherence among the different drought metrics in replicating drought severity. Accordingly, the current global assessment can contribute to the arising debate on the robustness of the different drought metrics, providing new evidences on CMIP6 model uncertainties for agricultural, ecological, and hydrological drought projections under a high-emission climate scenario.

2. Data and Methods

We employed monthly data of a set of hydroclimatic variables from the CMIP6 experiment (Eyring *et al*., 2016). These variables included precipitation, runoff, total column soil moisture, leaf area index (LAI) and net primary production (NPP). Data were provided for the historical period (1850-2014) and for the Shared Socioeconomic Pathway (SSP; 5-8.5) from 2015 to 2100. All CMIP6 individuals that secure data for the necessary variables, as well as the period 1850-

2100, were considered in our analysis (see Supplementary Table 1). Recalling that the CMIP6 outputs are provided in different native spatial resolutions, we interpolated data to a common resolution of 2.5° x 2.5°. To assess future projections in drought severity, our decision was made to consider the SSP5-8.5 scenario, which represents the worst possible scenario compared to the historical experiment.

The standardised drought indices were computed based on the common data inputs (e.g. precipitation, runoff, total column soil moisture, LAI and NPP). Nonetheless, other indices were computed using a combination of new variables. For example, maximum and minimum air temperatures, relative humidity, wind speed and solar radiation, were used to calculate AED following the Penman-Monteith FAO-56 equation (Pereira *et al*., 2015). Overall, based on these data and data of Evapotranspiration (Et), we calculated different indices using: i) the difference between precipitation and AED (P-AED), which is a metric that has been widely used for drought assessment since it summarises the balance between the water available in the form of precipitation and the existing AED (Vicente-Serrano *et al.*, 2010; Tomas-Burguera *et al.*, 2020a), ii) precipitation minus land evapotranspiration (P-Et), which is considered a long-term water budget and has been accordingly used to assess drought severity in several works (e.g. Padrón *et al.*, 2020), and iii) the difference between Et and AED (Et-AED), which compares the difference between the available water to evaporate and the water demand by the atmosphere (Kim and Rhee, 2016; Vicente-Serrano *et al.*, 2018) and is highly related to plant water stress (Stephenson, 1990). All these drought metrics were transformed into the same standardised units to make robust spatial and temporal comparisons. To fit data distribution, a log-logistic distribution was used , which is capable of standardising different climate and hydrological records under different climate conditions, as being evidenced in earlier works (e.g. Vicente-Serrano and Beguería, 2016; Vicente-Serrano *et al*., 2020a). The only exception was for precipitation, which was fitted to a Gamma distribution (Stagge *et al.*, 2015b). We tested the goodness of fit of the standardized indices using the coefficient of determination

(R^2) of the QQ plots, which compare the empirical probability distribution function (pdf) of each index and the pdf of the standard normal distribution. Results demonstrate that R^2 were almost close to 1 for majority of the world regions (Fig S1), with small deviations among the models (Fig S2) and for specific timescales (e.g. 3-month and 12-month). Afterwards, a second standardisation procedure was carried out independently for each of the 12 monthly series of the indices. To make this standardisation, both the mean and the standard deviation were computed for the reference period 1850-2014. This procedure minimizes the possible impacts of strong trends presented in the analysed variables for future scenarios in the possibility of calculating the drought indices (Vicente-Serrano et al., 2020a). Furthermore, this standardisation allows for a robust spatial and temporal comparability between the different metrics. Accordingly, drought duration and magnitude can be quantified for each time series and for the different indices. Drought events were identified using the run theory (Tallaksen *et al.*, 1997; Fleig *et al.*, 2006), considering a threshold of z = -1.28, which corresponds to a 10% probability of a standard normal observation being below that value. For drought event identification, all indices were computed at the 3-month time scale. To analyse the trends in the duration and magnitude of drought events, a linear regression model was fitted as a function of time, and the estimated slope was used to quantify the amount of change over time. The significance of these changes was assessed using the Mann–Kendall test (Kendall, 1948; Mann, 1945).

We analysed the relationship between the annual indices (computed at 12-month time scale) using the Kendall´s rank correlation coefficient, i.e., Kendall's τcoefficient (Kendall, 1938). This coefficient is a nonparametric measure of rank correlation that is more suitable than parametric statistics (e.g. Pearson's linear correlation coefficient) because it accounts for the non-linear relationships between variables.

For each grid point, the temporal agreement between the indices (computed at 12-month scale) was assessed by obtaining the percentage of simultaneous occurrence of years in which a pair of indices were below z=-1.28, thus producing a 2-dimensional representation of the results. Also, we computed the percentage of grid points where each pair of indices showed z-value below -1.28, resulting in a time series.

3. Results

3.1. Evolution of drought severity based on different metrics

Fig. 1 shows the evolution of the world land surface affected by drought between 1850 and 2100. It is computed as the percentage of land grid points below the 5th percentile of each raw (non-standardised) variable. This percentile is computed independently for each month, considering the 1850-2014 reference period. For all the variables, we found an increase in the world land surface impacted by drought from 1850 to 2010, albeit with some considerable spatial differences. Results demonstrate that precipitation, leaf area, and runoff will likely show a small increase of drought severity in future - scenarios. For precipitation-Et and NPP, the increase was mostly intermediate, although a sharp increase in NPP is noted between 2010 and 2030, followed by a constant behaviour to the end of the twenty-first century. For precipitation-AED, Et-AED and soil moisture, a remarkable increase is noted at the end of the century. As illustrated in Figs S3 and S4, some variables exhibited important seasonal and regional differences. For example, during the boreal winter season, drought based on NPP, soil moisture, and Et-AED increased. Rather, for precipitation and runoff, irrelevant drought increase was noted from 1850 to 2100. On the contrary, in the boreal summer season, the main drought increase was recorded for precipitation-AED, Et-AED, and soil moisture, with little increase for other variables (e.g. precipitation, runoff, and precipitation-Et).

Overall, we noted an increase in the magnitude of drought events that affects large areas of the world in terms of precipitation-AED, Et-AED, and soil moisture, albeit with significant spatial differences (Fig. 2). Interestingly, these three drought metrics showed a high agreement in terms of the areas that are likely to exhibit the highest increase in the magnitude of drought periods, including the Mediterranean region, Central America, northern South America and western South America, West Africa and South Africa. Nevertheless, it can be noted that the areas affected are much larger using Et-AED metric, with almost the entire land showing an increase in drought severity. Meteorological droughts, based on precipitation, showed an increase in drought magnitude in areas of Central and South America, West Africa, South Australia and the Mediterranean region, although this increase is not as high as suggested by other drought indices (i.e. Et-AED, and soil moisture). This pattern was almost similar when considering precipitation-Et, although some areas of South America did not show an increase in drought severity, suggesting that –in specific regions- the increase in drought magnitude can be reduced if Et is included in the calculations. Drought magnitude trends based on runoff showed smaller changes than considering exclusively precipitation, demonstrating that CMIP6 models project a less increase in the magnitude of hydrological droughts than in the magnitude of meteorological (precipitation) droughts. LAI did not show an increase in the magnitude of drought events in large areas of the world, except for parts of East Brazil. Thus, the spatial pattern was sparse on the global scale, with strong regional variability and a dominance of no changes or decrease in the magnitude of drought events in some regions (e.g., South America, Southeast Asia, Central Europe, and North America). Notably, the NPP-based assessment showed a strong reinforcement of drought magnitude in the high latitudes of the Northern Hemisphere. Rather, in some areas of Africa, South America and Southeast Asia, a decrease in the magnitude of the drought episodes, based on the NPP, was noted. .

Changes in the duration of drought events were almost similar to those of drought magnitude, particularly in terms of spatial patterns and the behaviour of the different drought metrics (Fig. S5).

Some drought metrics show high consistency in identifying positive trends in drought magnitude among the different models. Fig. 3 shows the percentage of models showing positive and statistically significant trends in drought magnitude between 1850 and 2100. As depicted, almost all models defined the same the regions with strong increase in drought magnitude considering precipitation-AED and Et-AED. This agreement was much lower for soil moisture, , even in large regions where the multimodel median values showed an increase in drought magnitude. A representative example is found in southern North America and South Africa, where multimodel medians showed a large increase in drought magnitude, while less than 40% of the models showed a positive and significant trend. In other regions wherea decline in drought magnitude was observed like northern South America or the Mediterranean, the percentage of models showing significant declining trends was roughly 50%, suggesting a strong uncertainty in model projections. Notably, although precipitation, precipitation-Et and runoff showed a drought increase in fewer regions than soil moisture, the consistency of this increase among models seems to be greater. More than 50% of the models suggested a positive and statistically significant increase in drought magnitude in northern South America and Central America, the Mediterranean and southern Africa for precipitation. A similar pattern was evident for vast areas in North and South America, Central Africa, and Central and South Asia when considering P-Et. This suggests that Et projections suppress the trend toward higher drought magnitudes in Southern Africa in comparison to precipitation-based projections, with only few models showing a positive and statistically significant trend. Interestingly, for runoff almost 50% of the models suggested a significant increase in drought magnitude in large regions of the Northern Hemisphere (e.g. Alaska, Labrador, Scandinavia, West Russia), while they did not witness a relevant increase in drought magnitude based on precipitation and precipitation-Et metrics. In the same context, apart from the high latitudes of the Northern Hemisphere, there were no regions where more than 30% of models showed an increase in drought magnitude for the NPP. Interestingly, results demonstrate that drought magnitude based on LAI will not change anywhere worldwide, with almost no model suggests significant changes.

Like drought magnitude, similar patterns of drought duration changes were observed globally (Fig. S6), with majority of the models suggesting no significant changes in ecological and agricultural droughts across majority of the world regions under scenarios of high greenhouse gas emissions.

The negative trends in drought magnitude (Fig. 4) and duration (Fig. S7) indicated few regions and metrics in which the models agree on a decrease in drought severity, mainly for precipitation in the high latitudes of the Northern Hemisphere. Even for LAI and NPP, the percentage of models that showed a decrease in drought magnitude is low. As depicted, although some areas, based on some metrics, showed a projected decrease in drought duration and magnitude with multimodel medians (e.g. Southeast Asia with LAI, Central Africa with the NPP, West Russia with soil moisture), there is still large inconsistency among the models. In the same context, while a steady increase in drought duration and magnitude was projected for some regions and variables, only few areas witnessed a decrease in drought duration and magnitude, irrespective of drought metric used. Thus, although there are important uncertainties between drought metrics and models related to the increase of drought duration and magnitude, there is a high consistency between models and metrics concerning drought decrease since drought magnitude and duration are not expected to decrease much under a scenario of high greenhouse gasses emissions.

3.2. Spatio-temporal relationships among drought metrics

In addition to knowing the consistency of trends between different drought metrics and models, it is also relevant to analyse the consistency of the temporal relationship in the drought severity based on these metrics (Fig. S8). As illustrated, we found strong annual relationships between some pairs of drought indices in the historical period. For example, the correlation was higher than 0.8 between precipitation and precipitation-AED and between precipitation and precipitation-Et in most areas of the world. Also, a high correlation was observed between precipitation-AED and precipitation-Et, with few exceptions, mainly in arid and semiarid regions where correlations decreased. Other pairs of drought metrics showed lower relationships on global scale, with important spatial differences. For example, the relationship between precipitation and Et-AED was only high in water-limited regions, where Et is mostly determined by water availability. It is worth mentioning that the relationship between precipitation (and also between the other climatic metrics) and soil moisture was low in most regions. Thus, the correlation with soil moisture was higher considering precipitation-AED and particularly Et-AED in regions like South America, Africa, and South Asia. LAI and NPP showed high correlations particularly in water-limited and cold regions. Nevertheless, these two ecological variables showed low correlations with the different meteorological drought metrics, suggesting that the interannual variability of agricultural and ecological droughts simulated by models is independent from those of climatic droughts in most regions of the world. This pattern was also observed considering soil moisture, with low correlations found between the interannual variability of soil moisture and the NPP and LAI in most regions, irrespective of biome types and bioclimatic conditions. The relationship between precipitation and runoff was high in most regions of the world, except for North America and most of Eurasia. In contrast, the relationship between interannual variability of runoff and soil moisture tended to be low globally, apart from the Mediterranean, northern South America, and Africa. Similarly, ecological metrics (i.e. NPP and LAI) showed low correlations with runoff worldwide.

Overall, these results suggest that, except for the high relationship between different climate metrics and their corresponding spatial differences that are mainly determined by the average water availability and temperature, the temporal relationship between different drought metrics was generally low in most regions of the world. This relationship was particularly low between climatic and vegetation metrics, as well as between soil moisture and other drought metrics.

The spatial pattern and the magnitude of the temporal relationships between the different variables did not show important changes considering future simulations (2015-2100), as compared with historical simulations (Fig. S9), albeit with some important exceptions (Fig. 5). For example, the relationship between the interannual variability of precipitation and other climatic drought metrics generally decreased, which is quite relevant in some areas of Central Asia considering precipitation-AED, but also in the Sahel and high latitudes of the Northern Hemisphere considering Et-AED. On the contrary, the relationship between precipitation and precipitation-Et remained stable for both the historical period and future. Also, we found a decrease in the relationship between precipitation-AED and precipitation-Et in some regions of Europe, South America, and Africa. The relationship between LAI and NPP was stable for the historical period and future simulations in most regions, albeit with a trend to reinforce in some regions. In addition, the relationship between precipitation and LAI tended to reinforce in the high latitudes of the Northern Hemisphere. This was also observed with the NPP, although a decline in the correlation between precipitation and NPP was observed in the Mediterranean, southern North America and northern South America. While the relationship between NPP and precipitation-AED was low during the historical period, this relationship was projected to decline further in the future, particularly in arid regions, the Amazon basin, and some wet areas of Africa. The decrease in the relationship with the NPP was even more severe when considering Et-AED, with an overall global decline. In addition, the relationship between NPP and soil moisture is likely to decline over large areas (e.g. the Mediterranean, northern South America, southern Africa, and Australia). Finally, the relationship of the runoff to other drought metrics tended to be stable between the historical period and the future high emission scenario, although a decreasing correlation with precipitation was observed in Scandinavia, and particularly with precipitation-AED and Et-AED in most Africa and the Amazon basin.

The temporal agreement in drought conditions among the different metrics is small in most regions during the historical period (Fig S10), suggesting that the annual drought conditions tend to differ noticeably between metrics. There was some agreement in the identified drought periods between precipitation and precipitation-AED, except in arid lands. A similar pattern was also noted between precipitation and precipitation-Et in wet regions and between precipitation-AED and Et-AED in arid lands. Nevertheless, the agreement in the occurrence of droughts between climatic, ecologic, and hydrologic metrics was small. Herein, it is worth to note that while our analysis is restricted to annual droughts to reduce the role of seasonality and the lags in the response of hydrological, agricultural and ecological drought conditions to meteorological droughts and irrespective of the physical consistency among models, drought periods mostly do not coincide in time among the different metrics. For the projected scenario, the temporal agreement between metrics shows some increase (Fig. S11). This is particularly relevant in some regions, such as the Mediterranean region, southern Africa, the Amazon basin, and Central America when comparing drought episodes recorded with precipitation and precipitation-AED, precipitation-Et, Et-AED and soil moisture and also between precipitation-AED and precipitation-Et and between Et-AED and soil moisture, particularly in water-limited regions. The agreement in the temporal identification of drought conditions also increases when comparing the climatic indices and the runoff in some areas, particularly in the Amazon and the humid regions of Africa, suggesting an agreement in annual droughts between some pairs of drought metrics, especially in water-limited or humid regions (Fig. 6).

The temporal agreement between annual droughts was low during the historical period between the different metrics, and also with low spatial agreement, suggesting that the global spatial patterns of annual drought severity usually did not agree between drought metrics (Fig. 7). The spatial agreement of drought conditions tends to increase under future climate change, in particular for some metrics (e.g. precipitation-AED and precipitation-Et, precipitation-AED and Et-AED, precipitation-AED and soil moisture). Nevertheless, the spatial agreement between droughts on the annual scale between climatic indices, runoff, and ecological droughts was low in both the historical experiment and the projected scenario, indicating spatial inconsistency in replicating annual droughts among the different drought metrics obtained from ESMs.

4. Discussion

This study analysed long-term evolution of different drought metrics on a global scale using CMIP6 models from 1850 to 2100. These metrics represent different climatic, hydrologic, and ecological variables. Results were presented for the historical experiment (1850-2014) and future projections (2015-2100) under a high-emission scenario (SSP5-8.5). While numerous studies assessed drought severity for future climate using CMIP6 models (e.g. Cook *et al*., 2020; Ukkola*et al*., 2020; Papalexiou*et al*., 2021; Wang*et al*., 2021; Guo*et al*., 2022; Zhao and Dai, 2022), our assessment employed a larger number of drought metrics, including climate-based (precipitation, precipitation-AED, precipitation-Et, Et-AED), hydrological-based (soil moisture and runoff) and plant physiology-based metrics (LAI and NPP). An evaluation of this variety of different metrics is essential to assess different drought types (meteorological, agricultural/ecological and hydrological) and to determine their consistency in terms of projected drought severity. Our results, as suggested by most models and drought metrics, suggest that drought would increase in southern North America, Central America, the Amazon region, the Mediterranean, southern Africa, and southern Australia, which agrees with earlier studies (e.g. Cook *et al*., 2020; Ukkola*et al*., 2020; Seneviratne*et al*., 2021; Wang*et al*., 2021; Zhao and Dai, 2022). Also, in accordance with previous studies (Cook *et al.*, 2020; Scheff *et al.*, 2021), our results showed important differences in drought projections as a function of drought metrics. For example, the use of AED-based drought metrics(e.g. the Standardised Precipitation Evapotranspiration Index (SPEI)) revealed that drought severity is likely to enhanced in future , as compared to those metrics based on precipitation, precipitation-Et, and runoff. This finding agrees with some investigations based on CMIP6 (e.g. Zeng *et al.*, 2022), and CMIP5 outputs (e.g. Cook *et al.*, 2014) and also by studies that employed other metrics like the Palmer Drought Severity Index (PDSI) (e.g. Scheff *et al.*, 2021; Yang *et al.*, 2021; Zhao and Dai, 2022). The different magnitude of drought as simulated based on hydrological (i.e. runoff) and climatic drought indices (which use AED in the calculations) is behind the overestimation of drought severity based on climatic indices under high emissions climate change scenarios as suggested by some studies(Berg and Sheffield, 2018; Scheff, 2018; Greve *et al.*, 2019; Berg and McColl, 2021).

While it can be argued that focusing on the metrics directly indicative of impacts in agricultural, ecological and hydrological systems (i.e. soil moisture, runoff, net primary production, and leaf area index) instead of climatic proxies of drought severity can be a more practical approach (McColl *et al*., 2022), we believe that models can show uncertainties in simulating complex hydrological and plant physiology processes. In addition, hydrological and ecological outputs from CMIP models could be affected by more uncertainty in comparison to climatic metrics that can be simulated easier, irrespective of any possible coupling mechanisms. For example, the spatial and temporal variability in soil moisture involves several processes, some of them are unknown, while others are difficult to simulate (van den Hurk *et al.*, 2011; Lu *et al.*, 2019). This may explain poor agreement between soil moisture observations and model simulations (Yuan and Quiring, 2017; Ford and Quiring, 2019). Streamflow generation is also very complex and models usually fail to simulate hydrological droughts (Tallaksen and Stahl, 2014; Barella-Ortiz and Quintana-Seguí, 2018). Plant physiology is also a key factor controlling both hydrological, agricultural and ecological droughts, and models show strong limitations and uncertainties in simulating plant physiological processes and water interchanges with soil and atmosphere (Liu *et al.*, 2020). These problems are even more important for future climate projections (Gentine *et al.*, 2019), given that other processes may introduce other sources of uncertainty (e.g. the role of atmospheric CO_2 concentrations) (De Kauwe *et al.*, 2021). Therefore, although some studies argue that plant and hydrological drought metrics obtained from model simulations can probably be more accurate than AED-based climatic indices, we believe that these metrics may also be affected by several strong uncertainties.

One of the novelties of our study is the use of diverse metrics, which is fundamental to address drought characteristics and impacts. In particular, we employed the Standardised Evapotranspiration Deficit Index (SEDI), based on the difference between Et and AED, which is informative on plant water stress (Kim and Rhee, 2016; Vicente-Serrano *et al.*, 2018; Li *et al.*, 2019, 2020; Zhang *et al.*, 2019; Alsafadi *et al.*, 2022; Jiang *et al.*, 2022) with several biogeographic implications (Stephenson, 1990). Changes in the SEDI, both in spatial patterns and drought severity, were almost similar, or even stronger than those obtained by the SPEI, and are characterised by an increase in drought severity under future scenarios of high anthropogenic emissions. In addition, we used two eco-physiological metrics, LAI and NPP, which have been considered by few studies as metrics of drought severity in model simulations(e.g. Scheff et al., 2021). As opposed to the SEDI, our assessment based on the LAI and NPP did not suggest an increase in agricultural and ecological drought severity, except for the high latitudes of the Northern Hemisphere. This may be explained by the role of snow and permafrost melt processes that could affect water availability (Chen *et al.*, 2021).

The picture provided by our eight drought metrics showed some paradoxical projections that are difficult to explain by coherent hydrological and plant physiological processes. In particular, different studies focusing on plant physiology have highlighted that plant mortality will strongly increase in future as a consequence of increased plant water stress and air temperature (e.g. Williams *et al*., 2013; McDowell and Allen, 2015; Xu*et al*., 2019; Brodribb*et al*., 2020). This assessment is consistent with observations of ecological and agricultural impacts of droughts, which are clearly reinforced by the observed increase in AED (Breshears *et al.*, 2005, 2013; Allen *et al.*, 2010; Carnicer *et al.*, 2011; Lobell *et al.*, 2011; Asseng *et al.*, 2015; Sánchez-Salguero *et al.*, 2017). Nevertheless, in opposition to this empirical evidence and the strong increase of drought severity as suggested by some climatic indices, LAI-based drought projections suggested that –in few cases where precipitation is projected to increase(e.g. Central America, southwestern Australia and the south of the Amazon region), drought severity is likely to increase in future simulations.

The limited increase in drought severity based on ecological metrics is difficult to be supported according to the widely known response of plants to water availability (Vicente-Serrano *et al*., 2020b) and atmospheric water demand (Breshears *et al.*, 2013; Grossiord *et al.*, 2020), particularly in water-limited regions where meteorological droughts (e.g. southern Africa, southern North America, and the Mediterranean), and AED are projected to increase (Scheff and Frierson, 2015; Vicente-Serra*no et al*., 2020d). These conditions can lead to a remarkable increase in plant water stress incompatible with increases in LAI and NPP. Thus, the only way to avoid changes in ecological droughts in water-limited regions, where climate aridity is projected to increase, is probably related to the physiological effects of the atmospheric CO_2 concentrations (Mankin *et al.*, 2017; Gonsamo *et al.*, 2021; Scheff *et al.*, 2022). Several studies have showed a reduction in the leaf stomatal conductance and plant resistance to water stress in response to enhanced atmospheric CO_2 concentrations (e.g., Ceulemans and Mousseau, 1994; Ainsworth and Long, 2005; Donohue *et al.*, 2013; Green *et al.*, 2020). However, the effects of increasing CO_2concentrations on ecological and agricultural drought severity are very complex (Allen *et al.*, 2015; De Kauwe *et al.*, 2021), and there are still several uncertainties in the assessment of these effects based on ESMs (Gentine *et al.*, 2019; De Kauwe *et al.*, 2021), tended to overestimate the effects of increasing CO_2 concentrations on plant physiology (Kolby Smith *et al.*, 2015; Marchand *et al.*, 2020; Zhao *et al.*, 2020). Moreover, CO_2 effects would not ameliorate plant stress during periods of water deficit, given that leaf stomatal conductance would not be controlled by CO_2 concentrations, but mostly by soil moisture content (Morgan *et al.*, 2004; Xu *et al.*, 2016; Menezes-Silva *et al.*, 2019). Therefore, our assessment of future agricultural and ecological droughts based on model simulations is highly uncertain given the current evidence of the responses of plants to enhanced water stress and AED and the several sources of uncertainty in the modelling of the carbon cycle by the ESMs (Padrón *et al.*, 2022). Thus, it is difficult to argue that ecological droughts will not increase in areas in which models suggest a strong decrease in precipitation and a remarkable increase in AED.

For hydrological drought projections, our study indicates that future projections of droughts quantified with soil moisture tend to resemble the pattern of the projections of drought severity using SPEI. This seems to disagree with some previous studies that had suggested less increase in soil moisture deficits than the decrease in meteorological indices including AED in future drought projections (Milly and Dunne, 2016; Berg and Sheffield, 2018). This disagreement can basically explained by the different statistical methods used to assess future projections. These models are strongly affected by the autocorrelation of the drought metrics, as well as by focusing on changes in the average values versus the tails of the complete set of the distribution values (Vicente-Serrano *et al.*, 2020a). Thus, the last IPCC report has showed a strong increase in drought severity worldwide based on extreme events of the total column soil moisture, particularly during the boreal summer season (Seneviratne *et al.*, 2021). This increase in the duration and magnitude of soil moisture deficits would be coherent with an increase in agricultural and ecological drought severity, even more considering the strong increase in AED, as projected by the CMIP models (Scheff and Frierson, 2015; Vicente-Serrano *et al*., 2020d), which would cause enhanced plant stress. Also, uncertainties in the projected Et are noticeably affect drought projections based on precipitation-Et, which is usually considered a metric of water availability. Thus, it is curious that the projections of meteorological droughts based on precipitation showed a stronger increase in drought duration and magnitude than projections based on precipitation-Et and runoff. It would be expected that hydrological droughts will not increase at similar rates of agricultural and ecological droughts, in response to increased AED. This is basically because the response of streamflow to enhanced AED is expected to be lower than to precipitation, as observed with streamflow data (Ficklin *et al.*, 2018; Yang *et al.*, 2018; Vicente-Serrano *et al.*, 2019). This issue has been well-established based on the ESMs, as runoff simulations mostly respond to precipitation at short time scales (Scheff *et al.*, 2022). However, even responding more to precipitation than to AED, it is difficult to support a smaller increase in drought severity by runoff than by precipitation under scenarios of a high increase in AED. This behaviour would be mostly explained by the suppression of Et as a consequence of the decreased leaf stomatal conductance given the enhanced atmospheric CO_2concentrations, which would reduce the severity of hydrological droughts (Roderick *et al.*, 2015b; Milly and Dunne, 2016; Yang *et al.*, 2019). However, a main constrain of this assessment is that the influence of this mechanism on future Et is highly uncertain in ESMs (Vicente-Serrano *et al*., 2022a). Moreover, Et is also observed to increase during dry periods (Zha*o et al*., 2022) and evaporation in surface water bodies is expected to increase in future scenarios (Wang *et al.*, 2018). For these reasons, it is difficult to argue that hydrological droughts quantified using precipitation-Et and runoff will increase less than meteorological droughts, based on precipitation, in future scenarios.

In addition to the comparative assessment of drought trends based on different drought metrics, another aspect of novelty in our study is that it assesses the spatial and temporal relationship between different drought metrics under the historical experiment and future SSP5-8.5 scenario. Specifically, we found that the temporal relationship between the precipitation-based climatic metrics (i.e. precipitation, precipitation-AED, and P-Et) is high worldwide, with some spatial exceptions (e.g. in water-limited regions for P-Et). This behaviour is expected given that precipitation is a main controller of the interannual variability of drought conditions(Vicente-Serrano *et al.*, 2015; Tomas-Burguera *et al.*, 2020b). For example, in the case of SPEI, precipitation explains more than 90% of the variability of this index, while AED is only relevant during periods of precipitation deficit, particularly in water-limited regions

(Tomas-Burguera *et al*., 2020b). This main role of precipitation is also observed in other drought indices such as the PDSI (van der Schrier *et al.*, 2013; Vicente-Serrano *et al.*, 2015). On the other hand, under the SSP5-8.5 scenario, the correlation between precipitation and AED-based drought indices is expected to decrease, suggesting a greater role of AED. Nevertheless, this temporal relationship remains high in most world regions.

The close relationship found between climate drought indices in historical and future simulations contrasts with the low correlations found between climatic and ecological drought indices, given the low percentage of years when drought conditions coincide following meteorological and ecological metrics. The interannual variability of LAI and NPP showed high agreement in both the historical period and in the future scenario. This is in agreement with observations recorded in the last decades using vegetation activity from satellites (as a surrogate of the leaf area) and tree-ring growth (as a surrogate of NPP) (Vicente-Serrano *et al*., 2016, 2020c). Nevertheless, unexpectedly, we noted a poor relationship between the temporal evolution of both LAI and NPP and the climatic drought indices, albeit with the use of a wide set of metrics used here that highly represent plant water stress conditions (e.g. Et-AED). Moreover, this low relationship is also found between the ecological variables and soil moisture, which is one of the main factors controlling vegetation activity and carbon uptake worldwide (Green *et al.*, 2019). This low relationship between climatic indices (and soil moisture) and ecological metrics could be explained by the uncoupling between water availability and plant water requirements as a consequence of the physiological effects of atmospheric CO_2 concentrations (as discussed above). Nevertheless, low interannual correlations were also found in the historical experiment. We consider that the low relationship between ecological drought metrics and climatic and soil moisture metrics introduces another important source of uncertainty in the assessment of the drought severity under future climate scenarios. It is expected that the agreement between NPP, LAI, and the different climatic metrics and soil moisture should be high, given the climate forcings used in the historical experiment. Thus, based on different vegetation metrics, numerous studies found strong temporal correlations between climate drought indices and soil moisture and different ecological measurements in the past decades, including satellite metrics (e.g. Vicente-Serrano *et al.*, 2013; Bachmair *et al.*, 2018), and tree ring growth (e.g. Orwig and Abrams, 1997; Vicente-Serrano *et al.*, 2014). This unexpectedly low correlation between climatic droughts, soil moisture deficits and agricultural and ecological droughts during the historical experiment suggests that the temporal decoupling between these metrics is not related to the possible physiological effects of the enhanced CO_2 concentrations. Rather, it can probably be due to the existing limitations of the models in reproducing the real physiological response of vegetation to drought. In addition to the low temporal concordance, there is a general spatial disconnection between the occurrence of climatic and ecological droughts in different regions worldwide.

The temporal agreement between climatic drought metrics, soil moisture, precipitation-Et, and runoff is also low, both in the historical experiment and the SSP5-8.5 scenario. With the exception of the tropical and subtropical regions in the case of runoff, the remaining world showed low correlations with climatic metrics. Thus, the temporal correlations were low between the interannual variability of soil moisture and runoff in most regions of the world. This suggests that, considering climatic and hydrological drought metrics, the consistency of ESMs simulations on long temporal scales (i.e. annual) may be also affected by uncertainties. Thus, as opposed to CMIP6 outputs, the interannual variability of observed soil moisture and streamflow is highly consistent with climate variables in most basins of the world (Dai, 2021).

5. Conclusions

This study provided new evidence on the interannual relationships and long-term trends between drought types based on different drought metrics obtained from ESM simulations. The main conclusion is that the coherence of the trends and the interannual relationships between drought metrics show important uncertainties that can largely impact any robust assessment of drought projections under scenarios of enhanced emissions of greenhouse gases. Although some previous studies have suggested that the use of climatic drought indices could overestimate drought severity under future scenarios, this study indicates that projections based on hydrological (i.e. soil moisture and runoff) and ecological drought metrics (i.e. NPP and LAI) can introduce uncertainties and inconsistencies, particularly for the projected interannual relationship between drought metrics, as well as expected drought impacts under scenarios of high emissions of greenhouse gases and strong temperature increase. Still, there are several sources of uncertainty, particularly linked to the plant processes and the physiological influences of the enhanced CO_2 atmospheric concentrations, which have important implications for the assessment of both ecological and hydrological droughts in future scenarios. Recent evidence highlights increased drought effects on crop systems and natural environments in response to drought events characterised by warmer conditions (Breshears *et al.*, 2013; Williams *et al.*, 2013; Fontes *et al.*, 2018), but also hydrological implications given enhanced evaporation from crops, natural vegetation, and water bodies (Vicente-Serrano *et al.*, 2017; Friedrich *et al.*, 2018; Althoff *et al.*, 2020). Although the response of plant physiology and hydrological processes could change in the future, with more adaptive strategies to much warmer conditions leading to a reduction in the severity of hydrological, agricultural, and ecological droughts compared to climatic droughts conditions, these scenarios may be uncertain. Therefore, the same (or even greater) criticism could be made of the drought severity projections based on climatic drought indices using plant and ecological metrics, as these metrics do not seem to respond coherently in time and space to the occurrence of meteorological droughts and seem to underestimate the strong role of warming processes, already evident in some hydrological systems, but mostly in agricultural and ecological ones.

Drought severity projections are an extremely relevant topic with several environmental and socioeconomic implications, which deserves some scientific debate. Nevertheless, several studies based on models can present considerable uncertainties. Indeed, improving the knowledge and modelling of the complex processes involved could reduce these uncertainties, but we are probably still far from finding this solution. A focus on simple, but robust models, as suggested by McColl *et al.*(2022), could be a better approach to improve the assessment of future drought severity. However, this robust assessment may actually be simpler, as in future periods of precipitation deficits (anthropogenic or naturally=induced), the projected increased warming will cause more stress on hydrological and environmental systems as observed in near-present climate, irrespective of the projected trends in precipitation.

Data Availability Statement

The data from the CMIP6 models is available at the World Climate Research Programme (WCRP, https://esgf-node.llnl.gov/search/cmip6/).

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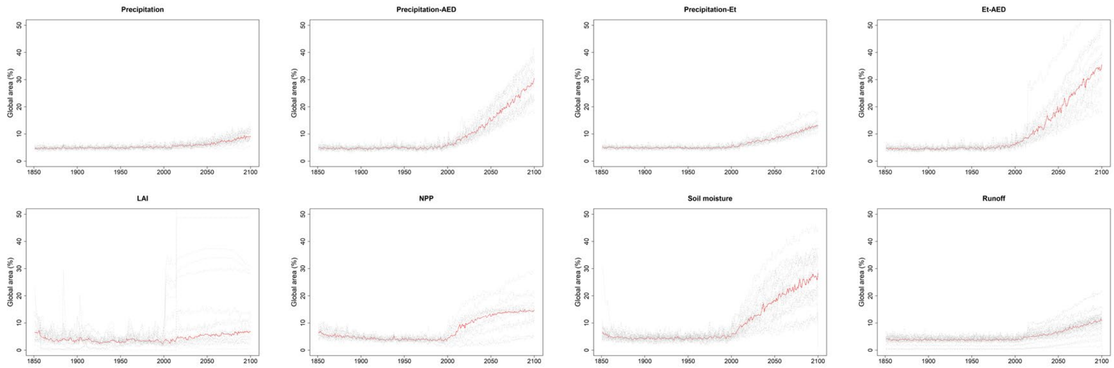


Fig. 1. Evolution of the annual average percentage of global land area affected by extreme dry conditions (5%) from 1850 to 2100. Grey lines represent the value for the different independent models and red lines refer to the median.

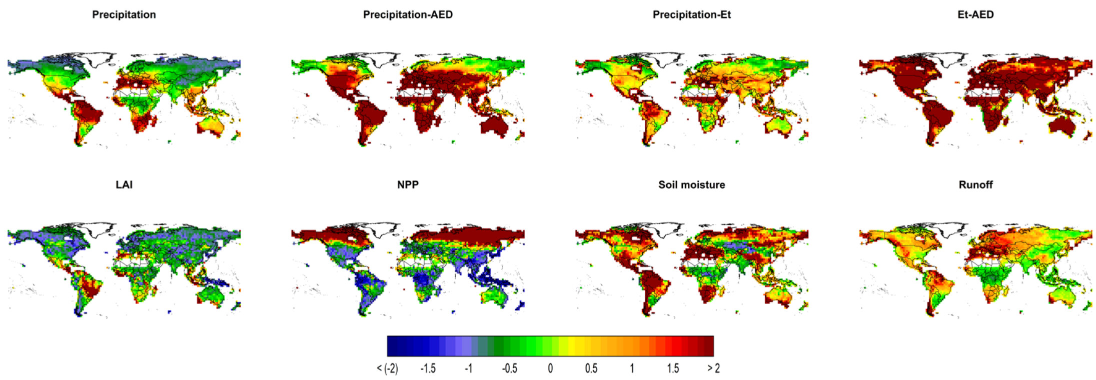


Fig. 2. Spatial distribution of the median trend in the magnitude of drought events between 1850 and 2100 (Factor: 100)

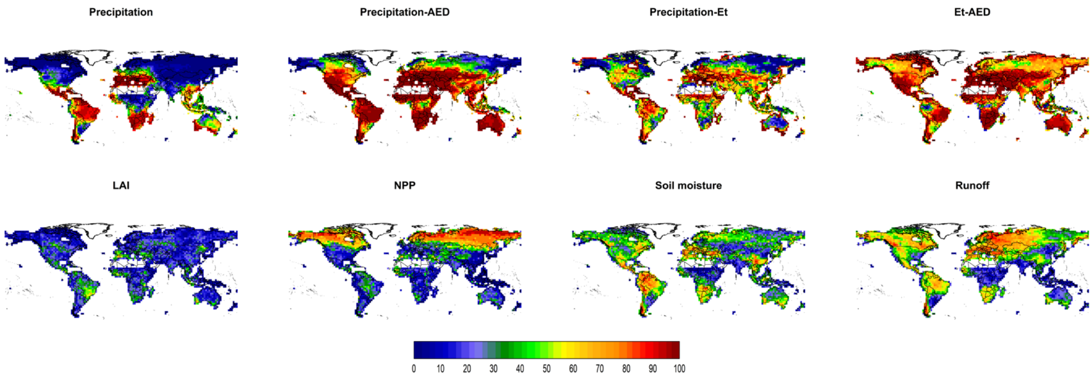


Fig. 3. Percentage of models showing positive and statistically significant trends in drought magnitude from 1850 to 2100

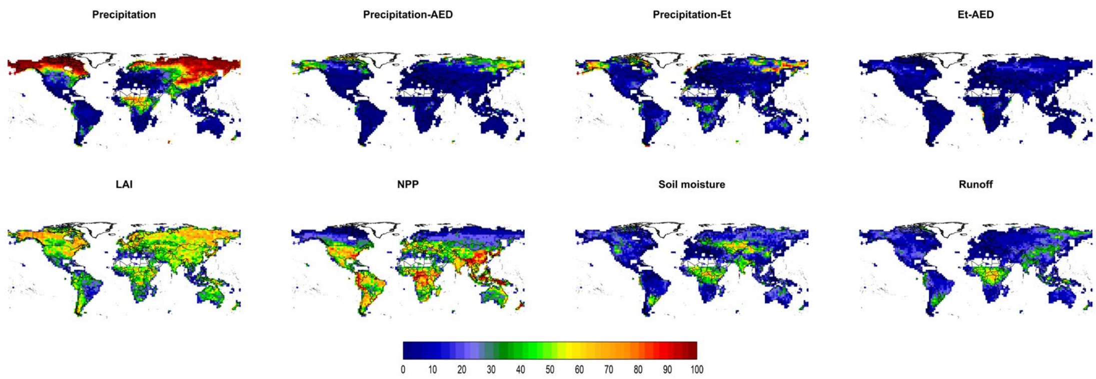


Fig. 4. Percentage of models showing negative and statistically significant trends in drought magnitude from 1850 to 2100

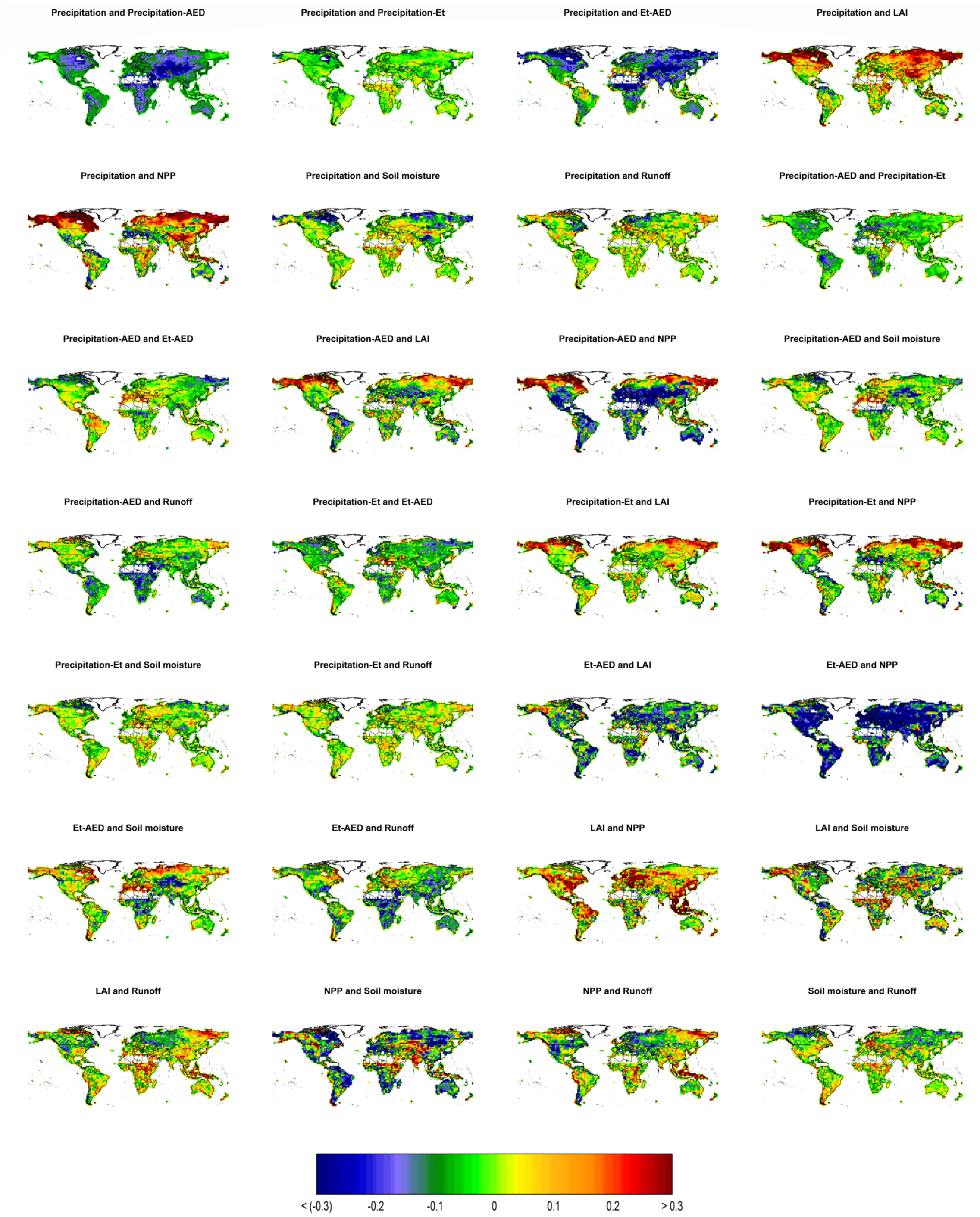
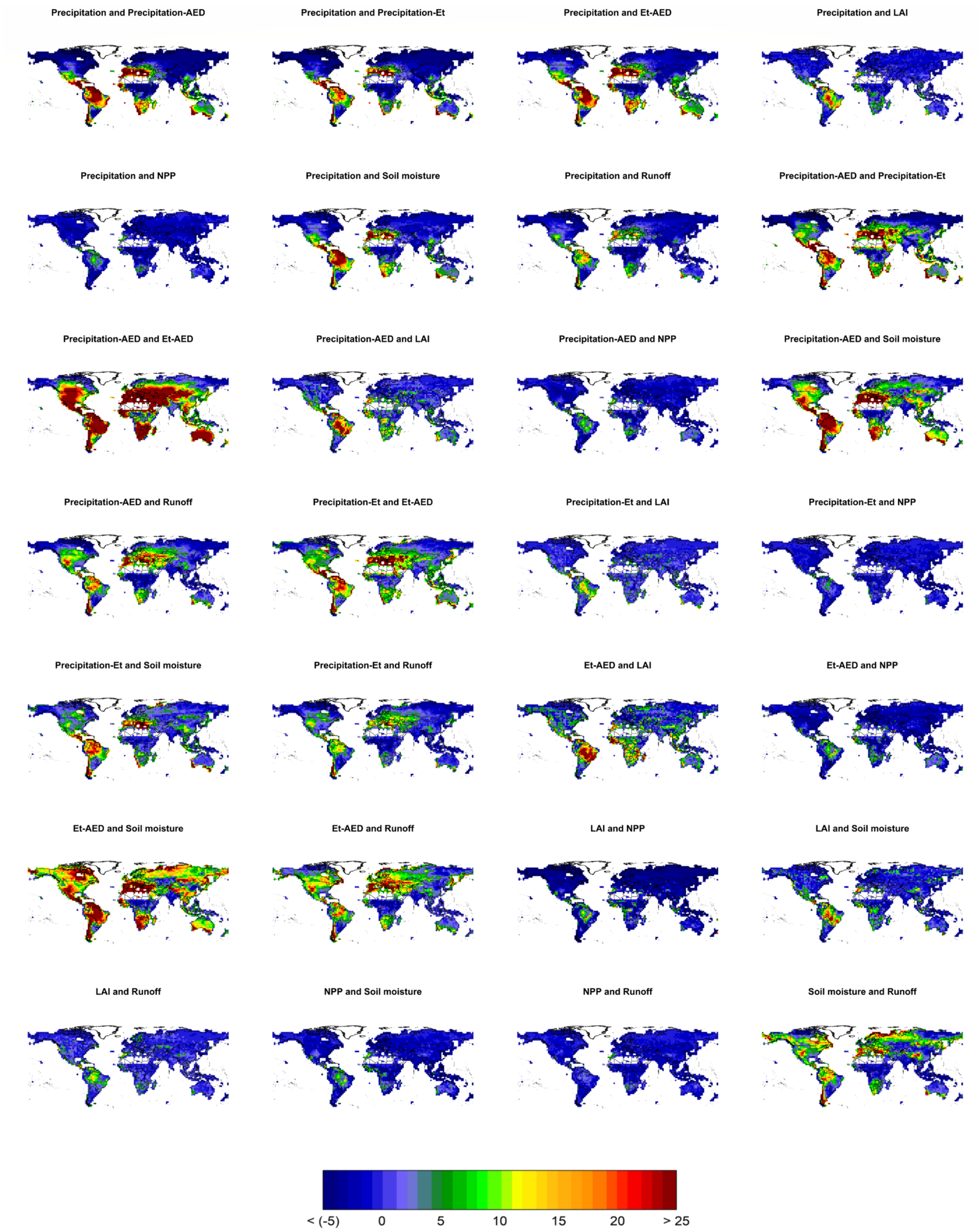


Fig. 5: Differences in the median Kendall's τ correlations between the projected (2015-2100) and historical period (1850-2014) for the different models



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1034 Fig. 6: Differences in the average percentage of temporal agreement among the different
1035 metrics between the projected (2015-2100) and the historical period (1850-2014) for the
1036 different models

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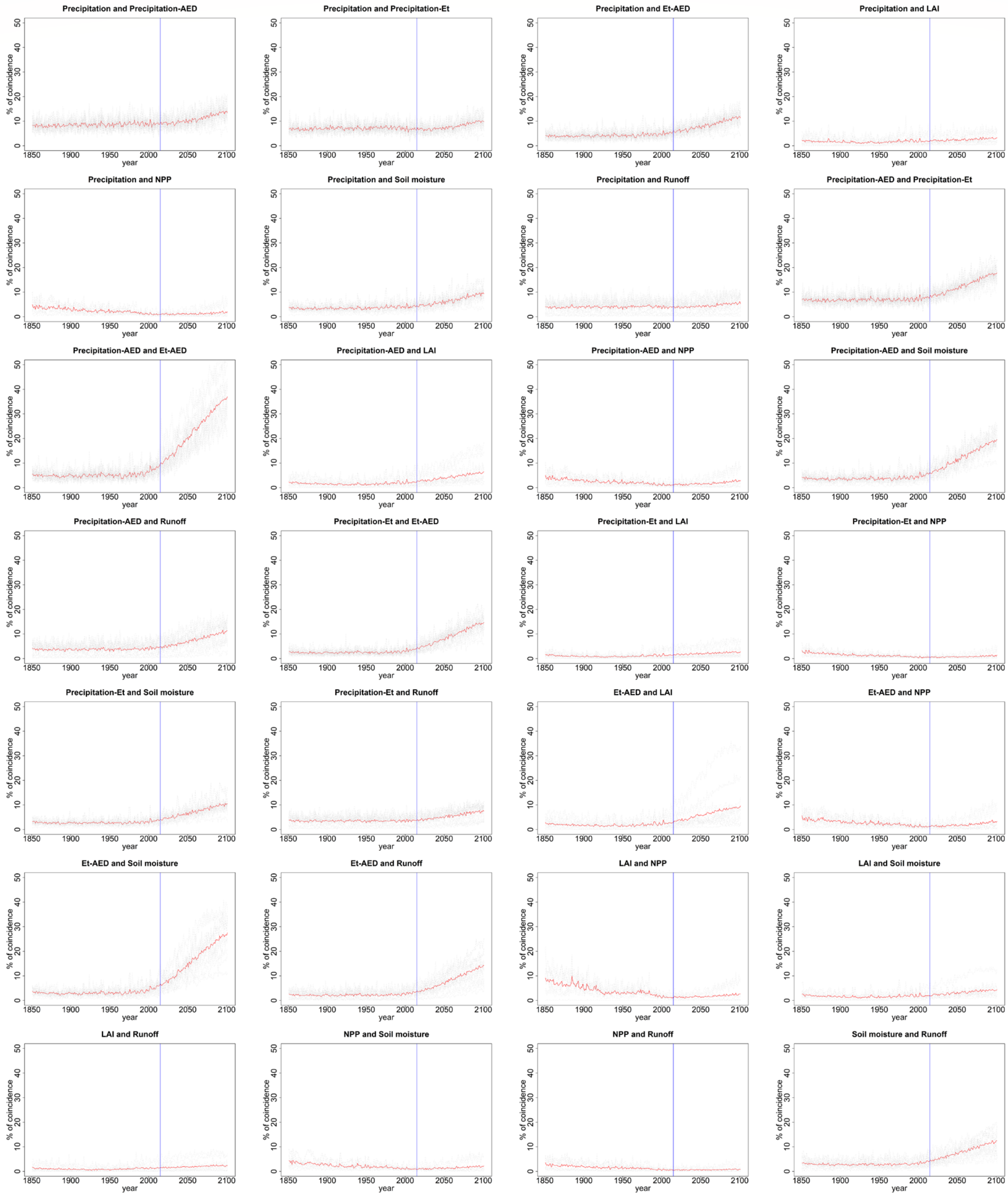

Fig. 7: Evolution of the spatial agreement of dry conditions between the different drought metrics.

Supplementary Information for:

Assessment of the global coherence of different types of droughts in model simulations under a high anthropogenic emission scenario

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Tables

Table 1: *CMIP6 models used in this study*

MODEL NAME	**INSTITUTION**	**NATIVE SPATIAL RESOLUTION** (lon x lat)
ACCESS-CM2	CSIRO-ARCCSS	1.875° x 1.25°
ACCESS-ESM1-5	CSIRO	1.875° x 1.25°
CanESM5-CanOE	CCCma	2.8125° x 2.767272°
CanESM5	CCCma	2.8125° x 2.767272°
CMCC-ESM2	CMCC	1.25° x 0.9424084°
CNRM-CM6-1-HR	CNRM-CERFACS	0.5° x 0.49512°
CNRM-CM6-1	CNRM-CERFACS	1.40625° x 1.38903°
CNRM-ESM2-1	CNRM-CERFACS	1.40625° x 1.38903°
FIO-ESM-2-0	FIO-QLNM	1.25° x 0.9424084°
GFDL-ESM4	NOAA-GFDL	1.25° x 1°
GISS-E2-1-G	NASA-GISS	2.5° x 2°
HadGEM3-GC31-LL	MOHC	1.875° x 1.25°
HadGEM3-GC31-MM	MOHC	0.8333333° x 0.5555556°
INM-CM4-8	INM	2° x 1.5°

IPSL-CM6A-LR	IPSL	2.5° x 1.267606°
MIROC-ES2L	MIROC	2.8125° x 2.767272°
MIROC6	MIROC	1.40625° x 1.38903°
MRI-ESM2-0	MRI	1.125° x 1.11209°

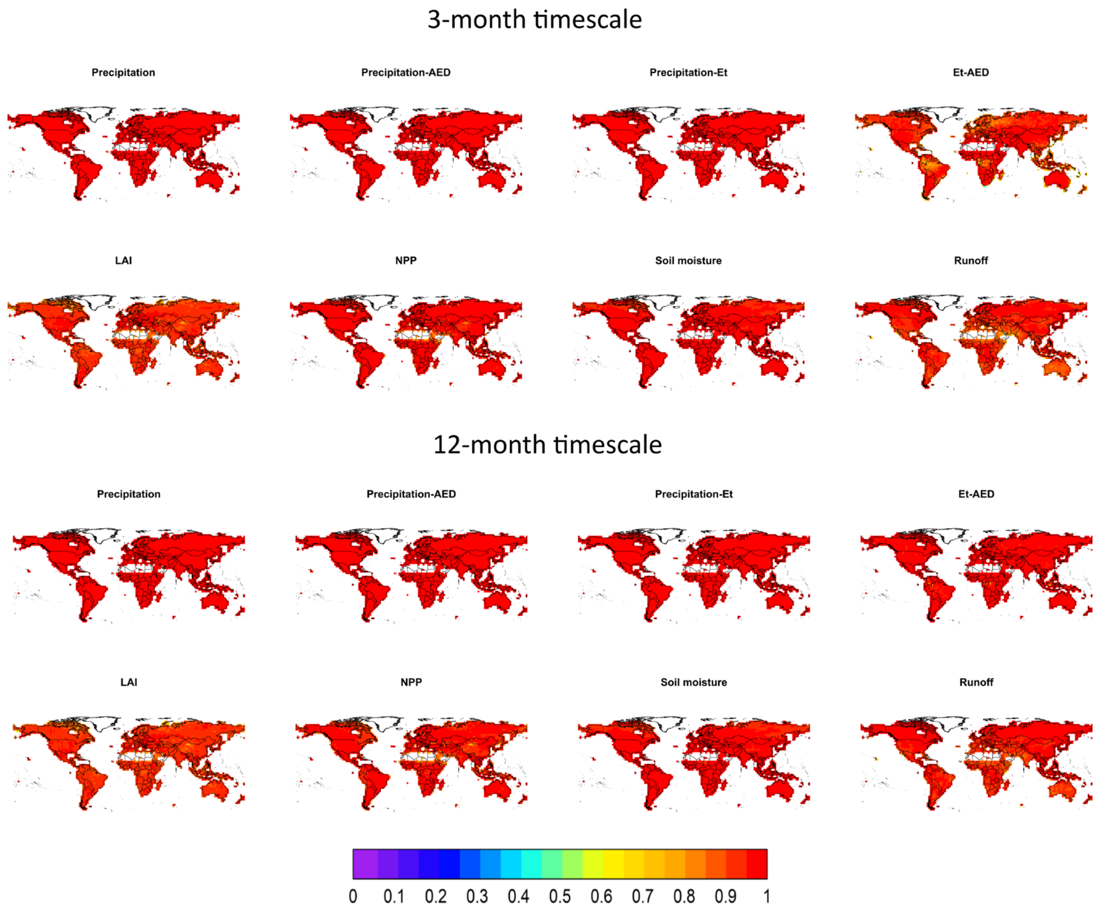

Fig. S1: Average R^2 of the standard normal QQ-plots used for assessing the fit of the index obtained by standardizing the studied variables by means of the log-logistic distribution (gamma distribution for precipitation)

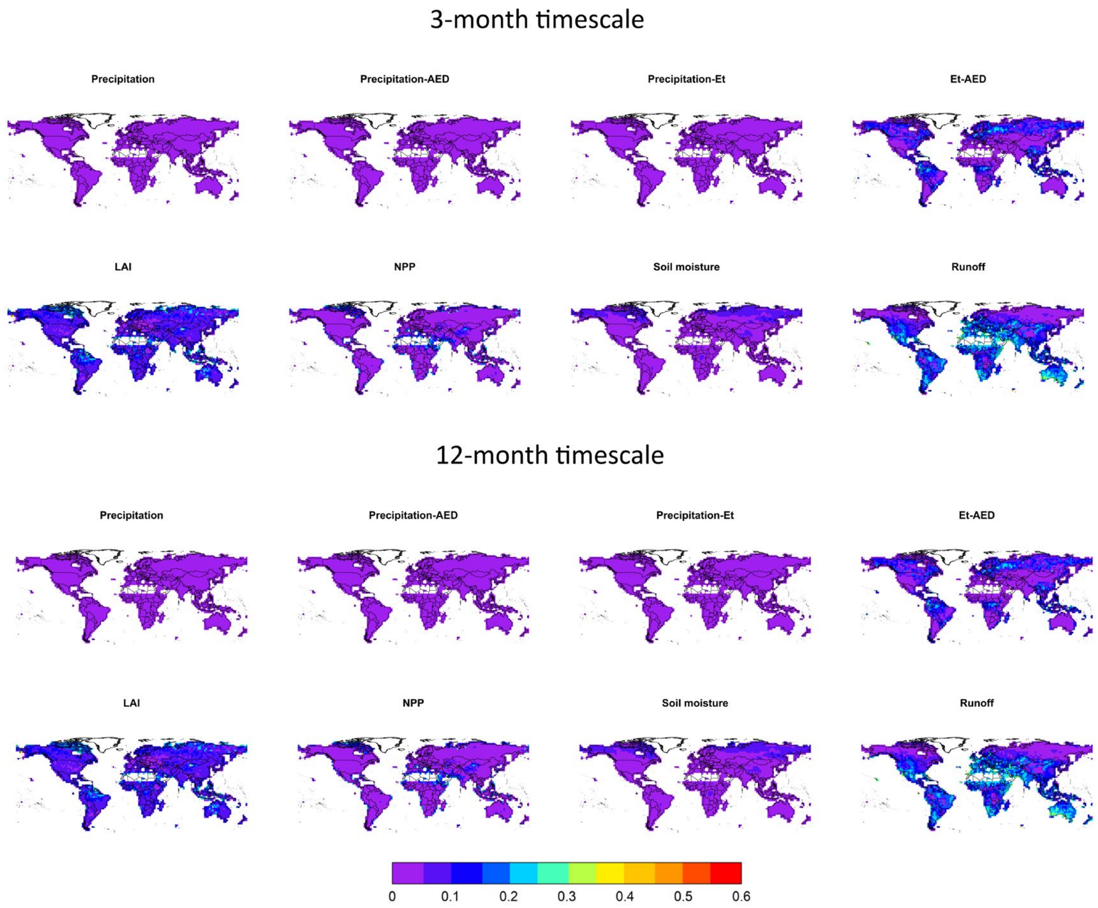

Fig. S2: Standard deviation of the values in Fig. S1

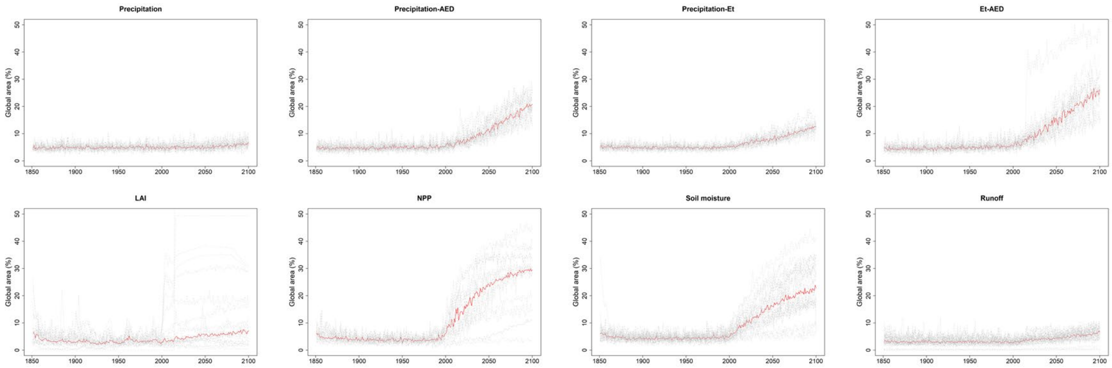

Fig. S3. Average percentage of global land area affected by extreme dry conditions. Same as Fig. 1, but for the evolution of the Boreal winter season (DJF).

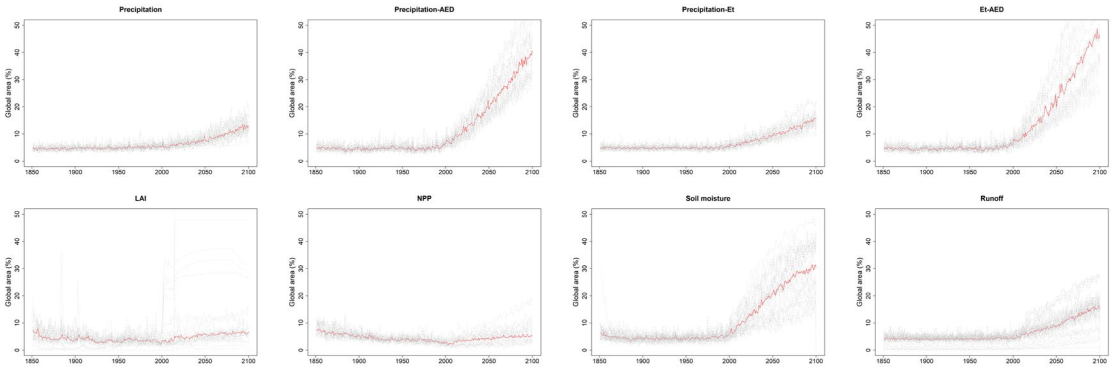

Fig. S4. Average percentage of global land area affected by extreme dry conditions. Same as Fig. 1, but for the evolution of the Boreal summer season (JJA).

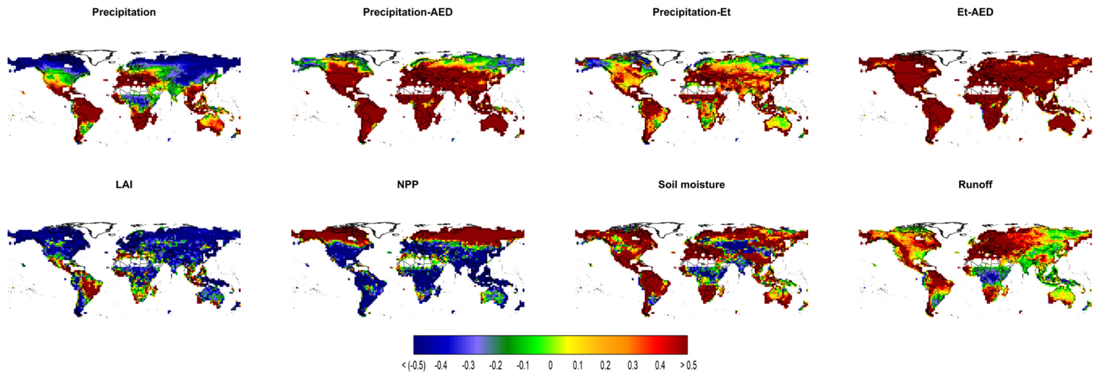

Fig. S5. Spatial distribution of the median trend in the duration of drought events between 1850 and 2100 (Factor: 100).

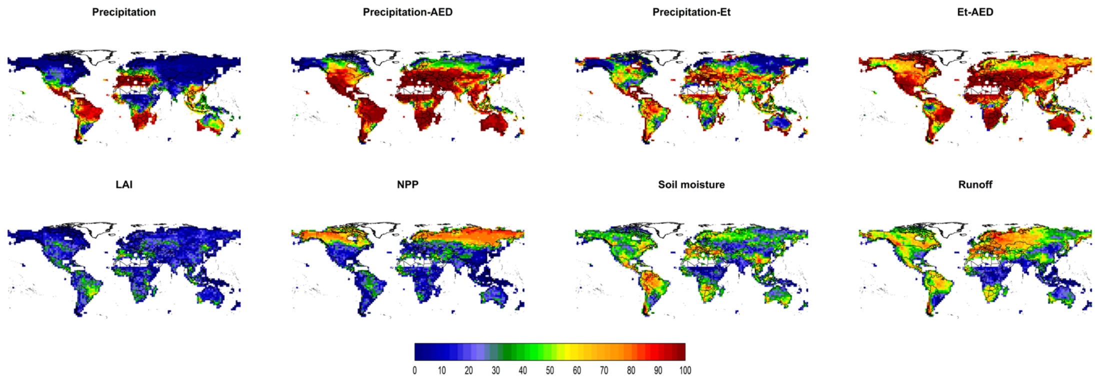

Fig. S6. Percentage of models showing positive and statistically significant trends in drought duration from 1850 to 2100

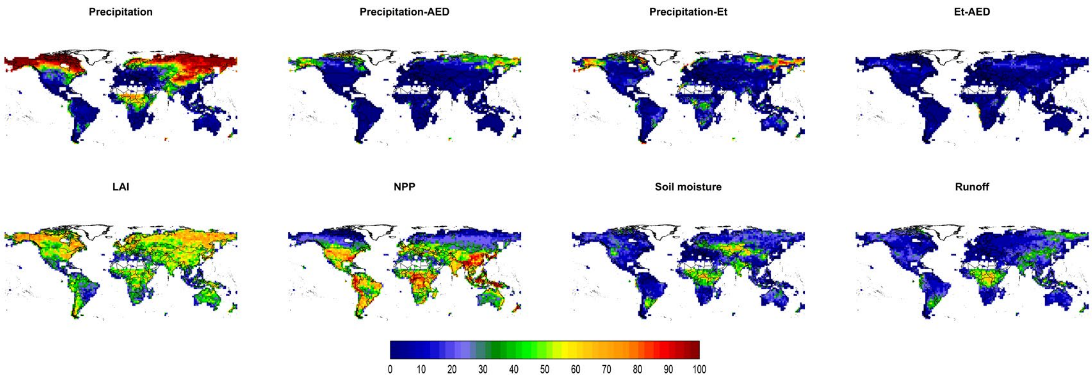

Fig. S7. Percentage of models showing negative and statistically significant trends in drought duration from 1850 to 2100.

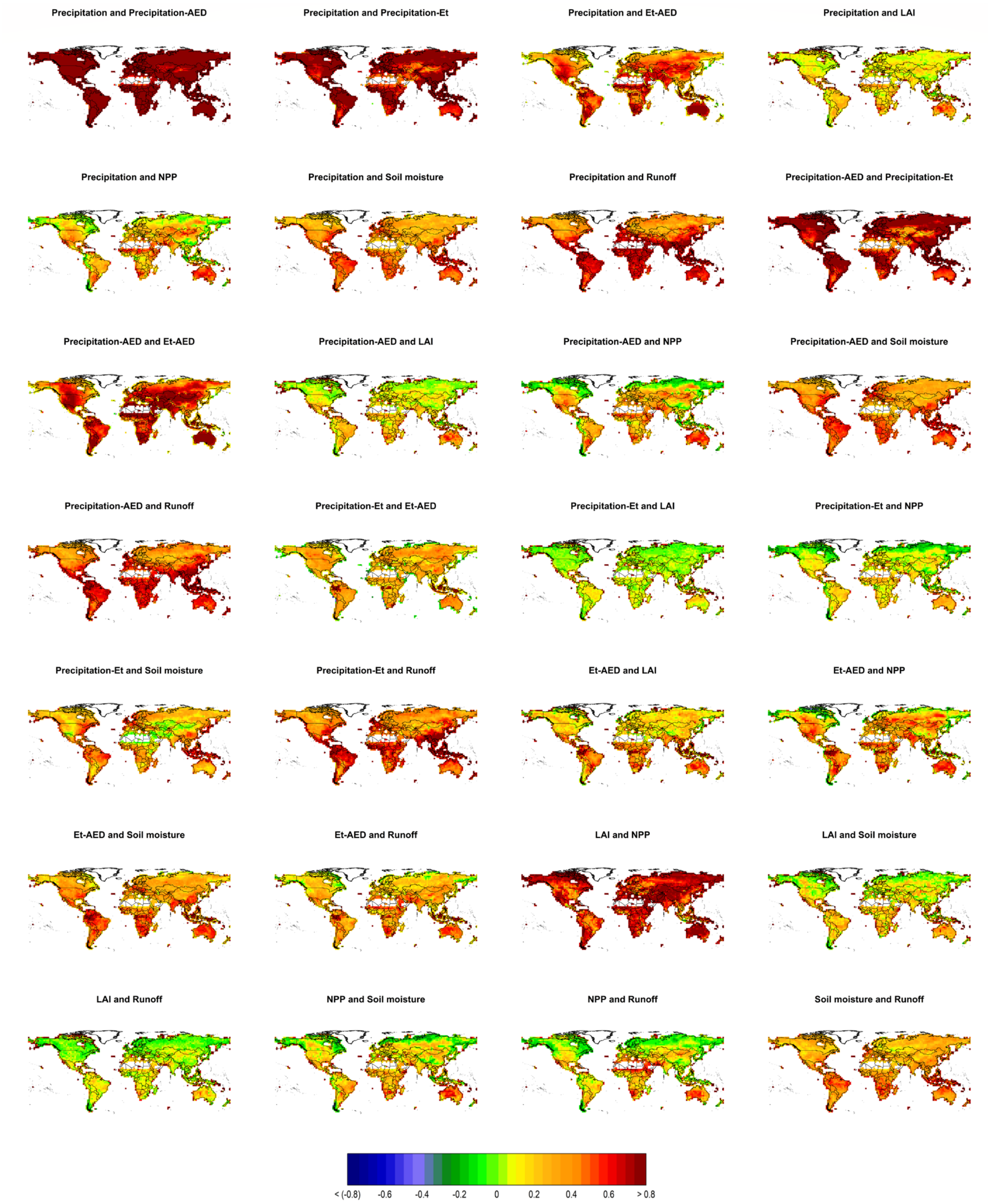

Fig. S8. Median Kendall's τ correlation in the historical period (1850-2014) among the various metrics for the different models

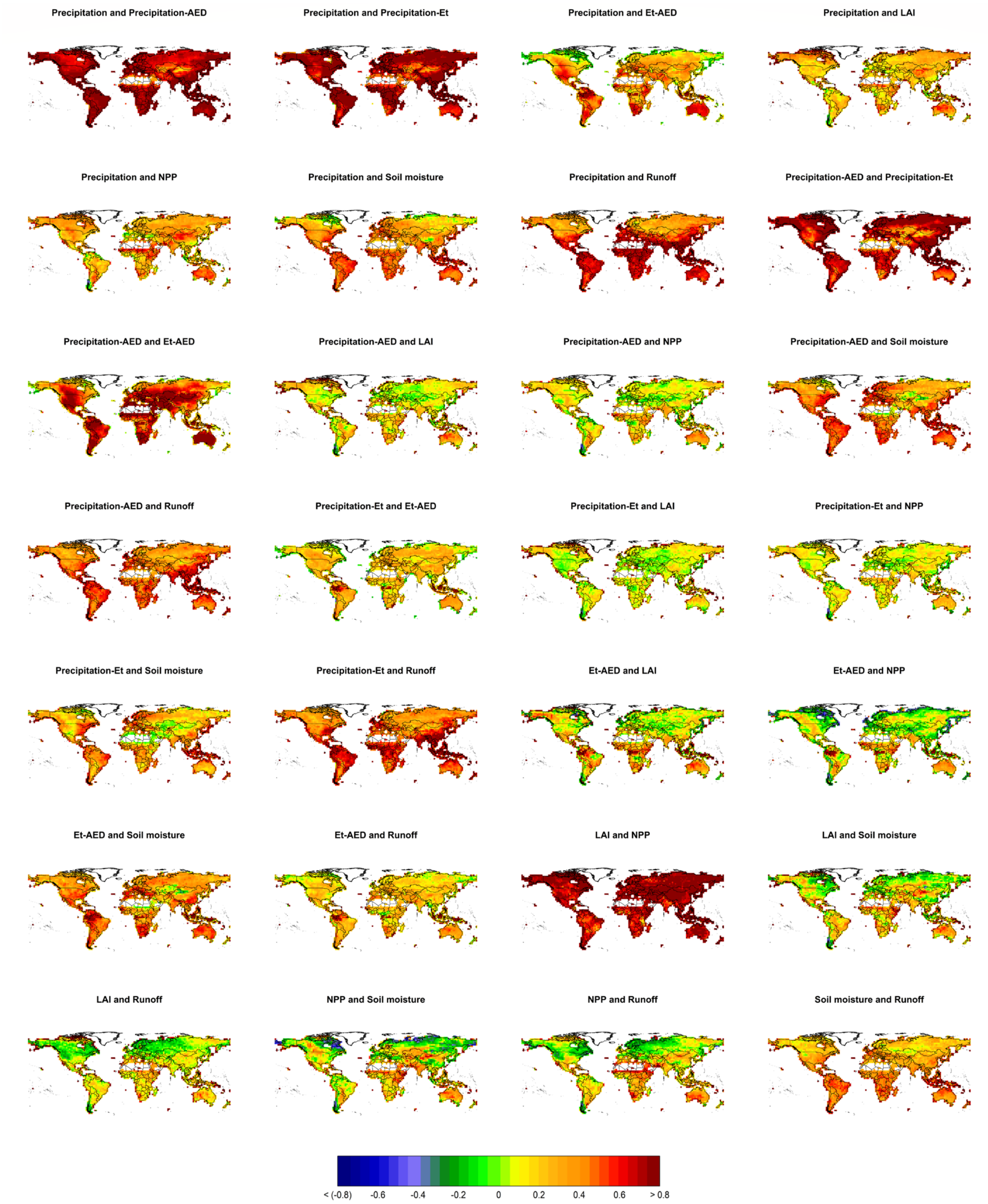

Fig. S9. Median Kendall's τcorrelation in the projected period (2015-2100) among the various metrics for the different models.

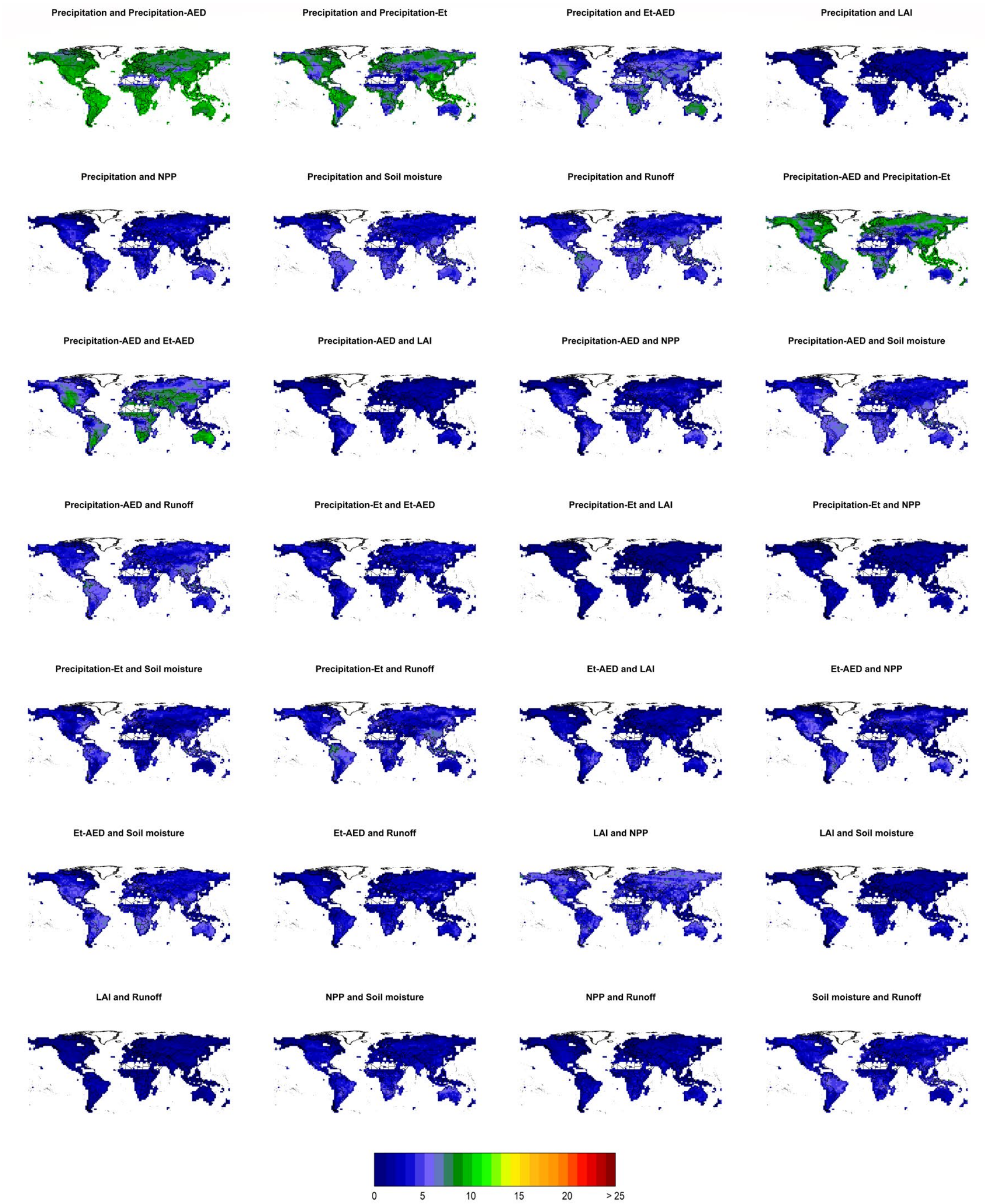

Fig. S10. Average percentage of temporal agreement among the various metrics in the historical period (1850-2014) for the different models.

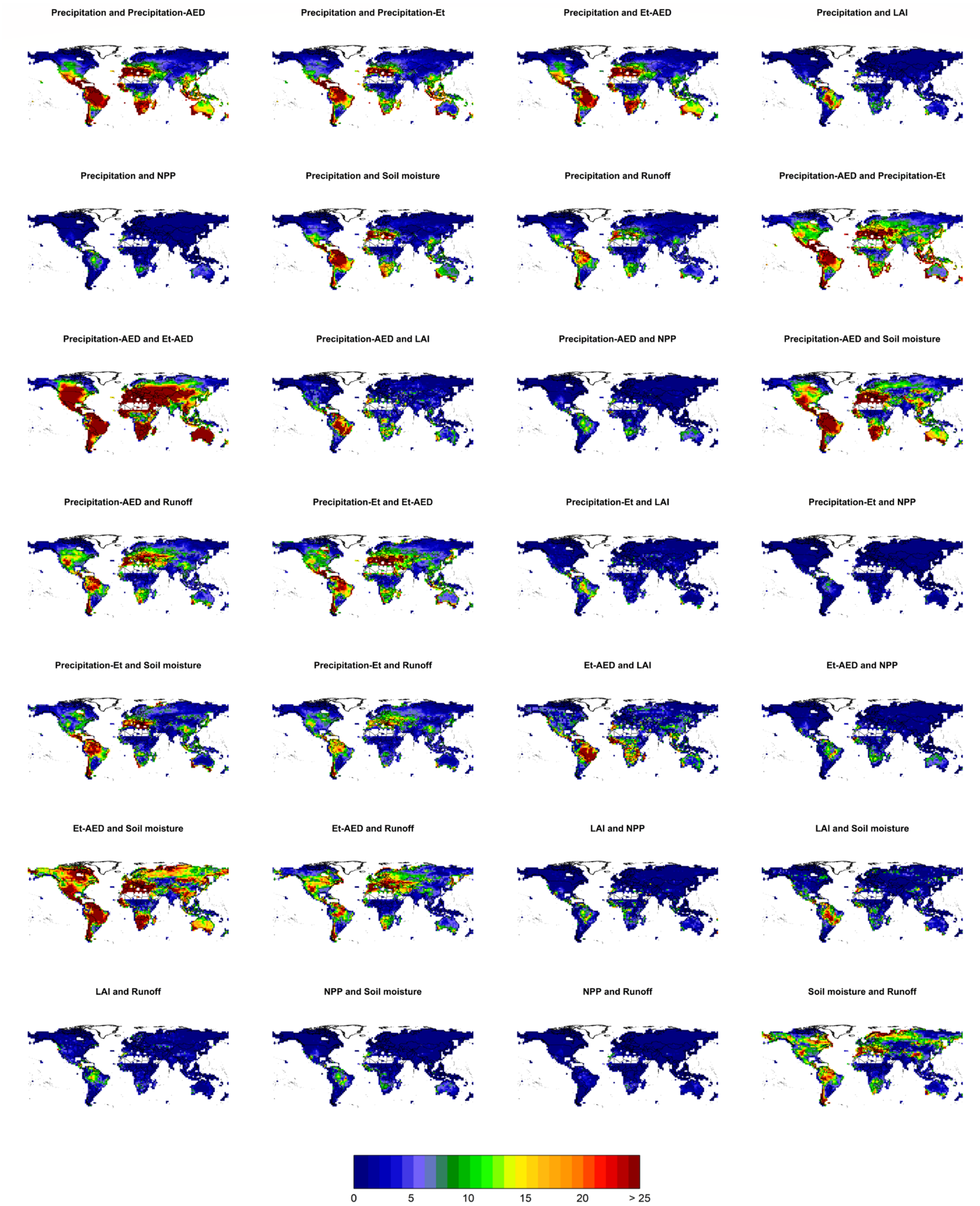

Fig. S11. Average percentage of temporal agreement among the various metrics in the projected period (2015-2100) for the different models.