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A quantitative evaluation of the issue of drought definition: a source of disagreement in future drought assessments

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Abstract

Droughts are anticipated to intensify in many parts of the world due to climate change. However, the issue of drought definition, namely the diversity of drought indices, makes it difficult to compare drought assessments. This issue is widely known, but its relative importance has never been quantitatively evaluated in comparison to other sources of uncertainty. Here, encompassing three drought categories (meteorological, agricultural, and hydrological droughts) with four temporal scales of interest, we evaluated changes in the drought frequency using multi-model and multi-scenario simulations to identify areas where the definition issue could result in pronounced uncertainties and to what extent. We investigated the disagreement in the signs of changes between drought definitions and decomposed the variance into four main factors: drought definitions, greenhouse gas concentration scenarios, global climate models, and global water models, as well as their interactions. The results show that models were the primary sources of variance over 82% of the global land area. On the other hand, the drought definition was the dominant source of variance in the remaining 17%, especially in parts of northern high-latitudes. Our results highlight specific regions where differences in drought definitions result in a large spread among projections, including areas showing opposite signs of significant changes. At a global scale, 7% of the variance resulted independently from the definition issue, and that value increased to 44% when 1st and 2nd order interactions were considered. The quantitative results suggest that by clarifying hydrological processes or sectors of interest, one could avoid these uncertainties in drought assessments to obtain a clearer picture of future drought change.

1. Introduction

Droughts are projected to intensify under climate change in many parts of the world (Madakumbura *et al* 2019, Zhou *et al* 2019, Padrón *et al* 2020, Takeshima *et al* 2020). The confidence level of drought projections for regions experiencing substantial drought intensification is considered relatively high. However, the overall confidence of drought projections is low to medium as noted in a series of reports from the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2012, 2014, 2018, 2019) because drought projections for regions experiencing insignificant changes entail insufficient agreement of projections of drought changes. Even though the recently published sixth assessment report of the IPCC working group I (AR6 WGI; IPCC 2021) concludes with high confidence that further global warming will expand land area affected by increasing drought frequency and severity, the confidence level for regional changes remains largely unchanged from the preceding assessment reports.

As one of the reasons for the confidence level, the IPCC reports underline that the diversity of drought definitions employed in drought studies has made it difficult to understand changes in diverse drought conditions (IPCC 2012, 2014, 2018, 2019). In particular, IPCC (2012) elaborates this difficulty in detail and calls it *the issue of drought definition*, a critical source of uncertainty in a meta-analysis on drought. Depending on the process of interest, drought can be defined for various hydroclimatic processes and is generally categorized as meteorological (precipitation), agricultural (soil moisture), or hydrological (runoff, river discharge, groundwater, reservoir) drought, as well as socioeconomic and ecological drought (van Loon *et al* 2016). Drought projections are highly dependent on a selected drought index. Because each drought index considers specific hydroclimate processes, the intersubstitutability of drought indices is low (Wanders *et al* 2017). However, many studies have been based on only one drought index or category, while it is also essential to better understand broad responses of the full hydrological cycle to warming. In addition, presumably due to data constraints, a drought indicator is sometimes used for different drought categories, e.g. a meteorological drought index is used for an agricultural application. Therefore, particular care is required when comparing drought studies to assess future drought conditions (IPCC 2012). It is necessary to be specific about hydroclimatic processes of interest in discussing broad drought studies. Nonetheless, the word 'drought' is often ambiguously used despite the multiple hydrological processes included.

To advance our understanding of future drought, decomposition of the associated uncertainty is indispensable. In assessing future drought, uncertainties arising from global climate models (GCMs), and greenhouse gas (GHG) concentration scenarios have been discussed (Orlowsky and Seneviratne 2013, Lu *et al* 2019). Additionally, widespread uncertainties result from terrestrial hydrological processes in impact assessment models (Prudhomme *et al* 2014). With respect to drought definitions, several studies have assessed future drought by using multiple drought indices to cover the multiple aspects of the climate change impacts on drought (Burke and Brown 2008, Orlowsky and Seneviratne 2013, Taylor *et al* 2013, Spinoni *et al* 2015, Touma *et al* 2015, Wartenburger *et al* 2017, Ukkola *et al* 2018, Wan *et al* 2018, Cook *et al* 2020, Vicente-Serrano *et al* 2020, Pokhrel *et al* 2021). These studies show that regionally, there are large differences in the sign and magnitude of drought changes among different drought indices. Hence, a definition mix-up can lead to misunderstanding when reporting or interpreting drought assessments. Taylor *et al* (2013) argued that it is crucial to understand the contribution of each source of uncertainty in drought assessments, including drought definitions. However, the relative importance of the definition issue compared to the other sources of uncertainty has never been quantitatively evaluated. Additionally, its spatial characteristics have not been thoroughly studied. For instance, Orlowsky and Seneviratne (2013) and Lu *et al* (2019) decomposed uncertainty in their drought projections and showed that the total uncertainty in soil moisture drought projection is dominated by uncertainty from GCMs. However, the drought definition issue and spatial information on the contribution of each source of uncertainty were not considered in either study.

Therefore, it remains unresolved how critical the issue of drought definition is to the overall variance of drought assessments relative to other sources of uncertainties. It is still a challenge to quantitatively understand where and to what extent the impact of warming could vary depending on definitions of drought. Such quantification enables an improved understanding of how much uncertainty one could avoid by specifically dealing with the drought definition. By focusing on three major drought categories and four temporal scales of interest among a wide variety of drought definitions, this study aims to quantify the relative importance of drought definitions in the variance in a future drought assessment and identify regions where such projections are sensitive to the definition issue. Consistently applying standardized drought indices for precipitation, soil moisture, and runoff, we investigated the uncertainties in our drought projections using a multi-model and multi-scenario dataset. This study attributes overall uncertainty to four sources: drought definitions, GHG concentration scenarios, GCMs, and global water models (GWMs).

2. Methods

2.1. Data

Monthly average precipitation, soil moisture, and runoff data from a multi-model hydrological simulation dataset produced by the Inter-Sectoral Impact Model Intercomparison Project Phase2b (ISIMIP2b; Frieler *et al* 2017) were examined globally for the period of 1861–2099. The simulations are from seven GWMs forced by bias-corrected climate projections from four GCMs (Lange 2019); consequently, 28 combinations of GWMs and GCMs (hereafter, ensemble members) were used. The seven GWMs included three global land surface models, CLM4.5 (Oleson and Lawrence 2013), JULES-W1 (Best *et al* 2011), and MATSIRO (Pokhrel *et al* 2015, Yokohata *et al* 2020); three global hydrological models, CWatM (Burek *et al* 2020), H08 (Hanasaki *et al* 2018), and WaterGAP2 (Müller Schmied *et al* 2014, 2016); and one dynamic global vegetation model, LPJmL (Rost *et al* 2008). Following the ISIMIP2b simulation protocol (www.isimip.org/protocol/#isimip2b), all GWMs performed simulations at a spatial resolution of $0.5^\circ \times 0.5^\circ$. The four GCMs represent a subset of those participating in Coupled Model Intercomparison Project phase 5 (CMIP5): HadGEM2-ES, IPSL-CM5A-LR, GFDL-ESM2M, and MIROC5. Note that a limited number of GCMs might not cover the full range of the CMIP5 model spread. However, upon data availability at that time, ISIMIP tried to select GCMs that reasonably range within the larger CMIP5 spread (Frieler *et al* 2017). The precipitation projections were taken from the same four GCMs. The soil moisture and runoff projections were based on the hydrological simulations available for each combination of GWMs and GCMs. Three GHG concentration scenarios, namely, the representative concentration pathways (RCPs) 2.6, 6.0, and 8.5 (Moss *et al* 2010), available in ISIMIP2b, were used. Thus, 12 samples of precipitation projections and 92 samples of soil moisture and runoff projections were investigated. Because the soil layer depth varies among GWMs, the soil moisture within the top 1 m below the land surface was consistently used. Following the priority simulation setting defined by ISIMIP2b, the cropland area, irrigation area, and reservoir distribution were fixed at the level of 2005 after 2005. Atmospheric feedbacks arising from water and land management were not considered in this study (Hirsch *et al* 2017, 2018, Thiery *et al* 2017, Hauser *et al* 2019).

2.2. Drought detection

The same concepts and consistent processes from widely used standardized methods were applied for precipitation, soil moisture, and runoff to estimate three traditional physical drought categories: standardized precipitation index (SPI; McKee *et al* 1993), standardized soil moisture index (SSI; Hao and AghaKouchak 2013), and standardized runoff index (SRI; Shukla and Wood 2008). For any given location and temporal accumulation scale of interest, standardized indices represent the anomalies on a normal distribution of a variable of interest. Given a variable, first, its long-term time series is fitted to a probability distribution and converted into a normal distribution. For each drought category, we applied the gamma distribution for fitting (Ukkola *et al* 2018). Then, we estimated standardized indices on four different accumulation temporal scales (hereafter, scale): scale-1, 3, 6, and 12 months. Generally, scale-3 and scale-6 are used for seasonal scale assessments, while scale-12 is used for investigations on an annual scale. Although the drought definition issue includes the selection of drought indices within a drought category, this study focuses on one drought index per drought category for simplicity and assumes that the drought definition is derived from drought categories and the temporal scale parameter. This study considers severe or extreme drought conditions (SPI, SSI, SRI < -1.5; the corresponding return period is longer than 15 years) based on the reference period of 1861–1960. This analysis climatologically assessed the total drought months during each period as a proxy of drought frequency. The differences between the pre-industrial period (1861–1890) and two future periods (mid-future; 2035–2064, far-future; 2070–2099) were evaluated.

2.3. Decomposition of variance

We applied a four-way multifactorial analysis of variance (ANOVA) to changes in the drought frequency to decompose the variance. The four variance sources included drought definitions, GHG concentration scenarios, GCMs, and GWMs. The drought definition was composed of drought categories and scales. Because these four factors are considered the primary causes of variance in drought assessments, these groups were established as the main factors. ANOVA was carried out for each grid cell. The overall variance denoted by the total sum of squares (TSS) is given as follows (Vetter *et al* 2015, Hattermann *et al* 2017):

$$\mathrm{TSS} = \sum_{i=1}^{N_{\mathrm{def}}} \sum_{j=1}^{N_{\mathrm{scn}}} \sum_{k=1}^{N_{\mathrm{gcm}}} \sum_{l=1}^{N_{\mathrm{gwm}}} \left(X_{ijkl} - \bar{X}\right)^2 \tag{1}$$

where X_{ijkl} is the specific value at a grid cell corresponding to drought definition i, scenario j, GCM k, and GWM l; $\bar{X}$ is the overall mean; and N is the number of samples of a factor. The overall variance was decomposed into 11 interaction terms, as well as four main effects that can be directly attributed to the drought definition, scenario, GCM, and GWM:

$$\begin{aligned}\mathrm{TSS} = {} & \mathrm{SS}_{\mathrm{def}} + \mathrm{SS}_{\mathrm{scn}} + \mathrm{SS}_{\mathrm{gcm}} + \mathrm{SS}_{\mathrm{gwm}} \\ & + \mathrm{SS}_{\mathrm{def*scn}} + \mathrm{SS}_{\mathrm{def*gcm}} + \mathrm{SS}_{\mathrm{def*gwm}} \\ & + \mathrm{SS}_{\mathrm{scn*gcm}} + \mathrm{SS}_{\mathrm{scn*gwm}} + \mathrm{SS}_{\mathrm{gcm*gwm}} \\ & + \mathrm{SS}_{\mathrm{def*scn*gcm}} + \mathrm{SS}_{\mathrm{def*scn*gwm}} \\ & + \mathrm{SS}_{\mathrm{def*gcm*gwm}} + \mathrm{SS}_{\mathrm{def*gcm*gwm}} \\ & + \mathrm{SS}_{\mathrm{def*scn*gcm*gwm}} \end{aligned} \tag{2}$$

where SS is sum of squares. The suffixes indicate the main factors involved in an interaction term. The interaction terms between two, three, and four main factors are referred to as the first-, second-, and third-order interactions, respectively. The main factor effect for the drought definition ($\mathrm{SS}_{\mathrm{def}}$) and its contribution rate ($\mathrm{CR}_{\mathrm{def}}$) to the overall variance are given as follows:

$$SS_{def} = N_{scn} N_{gcm} N_{gwm} \sum_{i=1}^{N_{def}} \left(\overline{X_i} - \bar{X} \right)^2 \tag{3}$$

$$CR_{def} = SS_{def} / TSS \tag{4}$$

where $\overline{X_i}$ is the mean over the indices j, k, and l for drought definition i. Equations for the interaction terms are given in supplementary equations (1)–(3) (available online at stacks.iop.org/ERL/16/104001/mmedia).

3. Results

3.1. Drought frequency projections for the three drought categories

For the far-future period, the total number of months under severe or extreme drought during the 30 years was projected to increase in many parts of the world (figure 1; scale-3). The results demonstrated that the three drought categories presented regionally varying spatial patterns of changes. A higher GHG concentration scenario showed a larger spatial extent of substantial increases in drought frequency. Regarding significant changes, the agreement in the sign of change among ensemble members (hereafter, the member agreement) tended to be high (>80%) throughout the three drought categories. On the other hand, extensive low member agreement (<60%) indicating large model uncertainty was also observed. Soil moisture and runoff drought showed a larger area with low member agreement than precipitation drought regardless of GHG concentration scenarios, which is consistent with preceding studies (Touma *et al* 2015, Berg *et al* 2017, Dai *et al* 2018, Ukkola *et al* 2018).

Regarding precipitation drought, regions with a substantial increase (>100%) in drought frequency were statistically significant (two-sided Kolmogorov–Smirnov test; $p = 0.05$; supplementary figure S1) in southwestern North America, parts of northern, central and southern South America, western and southern Africa, the Mediterranean to western Asia, Southeast Asia to Southern China, and southern Australia. These increases were consistent throughout the three RCPs. Large, widespread decreases (>50%) in parts of northern high-latitude regions in North America and Asia were also statistically significant. Low member agreement was found for parts of areas from Central Europe to Siberia, as well as East and South Asia and central Africa.

Soil moisture drought showed significant increases in larger areas than precipitation drought in eastern and northern North America, northern South America, northern Europe, central Africa and northern and eastern Asia, which was the case for all scenarios. Notably, in these regions with significant increases in soil moisture drought, precipitation drought did not show a robust change (i.e. low member agreement or statistically insignificant) or even a decrease. The results highlight that the increased atmospheric evaporative demand associated with a warmer climate is expected to play a critical role in soil dryness. Conversely, despite high member agreements over the northern high latitudes in precipitation, that of soil moisture drought was low.

In terms of runoff drought, widespread increases in the drought frequency were more similar to soil moisture drought than precipitation drought and extended into northern high latitudes. Nevertheless, the magnitude of change was moderate, and regions with substantial increases (>100%) were relatively sparse compared to the other two categories. For runoff, changes in snow processes also play a crucial role in high latitude and altitude areas. In the northern high latitudes, even though precipitation is expected to increase, snow accumulation is projected to decline owing to higher temperatures, and snowmelt is expected to shift earlier (Shi and Wang 2015). The results were assumed to include such a hydrological regime shift and its seasonal impact on drought conditions. In contrast to high member agreements in precipitation and soil moisture in parts of high latitudes, runoff drought showed low member agreements in the regions, such as North Europe and eastern Canada.

It must be noted that these changes in drought frequency include seasonality (supplementary figures S2 and S3, (a)–(i)). In general, larger areas with an increase in drought frequency were found during the summer season in the Northern and Southern hemispheres, respectively, which is more obvious in soil moisture and runoff drought. On the other hand and importantly, regions with a statistically significant increase in drought frequency tend to show a large increase throughout seasons. Overall, the seasonality in changes in drought frequency corresponds to changes in the long-term seasonal average or 10th percentile seasonal mean of base variables, namely, precipitation, soil moisture, and runoff. The spatial distribution of the changes in these base variable statistics was generally comparable to previous studies, including spatial characteristics of their model uncertainty (Cheng *et al* 2017, Yang *et al* 2017, Lu *et al* 2019, Cook *et al* 2020, Ukkola *et al* 2020, Zhou *et al* 2021). However, we also found that changes in drought frequency and the two base variable statistics are not necessarily consistent. For example, an increase in 10th percentile seasonal mean and an increase in drought months can occur simultaneously (supplementary figures S2 and S3, (j)–(o)). This is considered related to the temporal resolution of the statistics and changes in dry spell length.

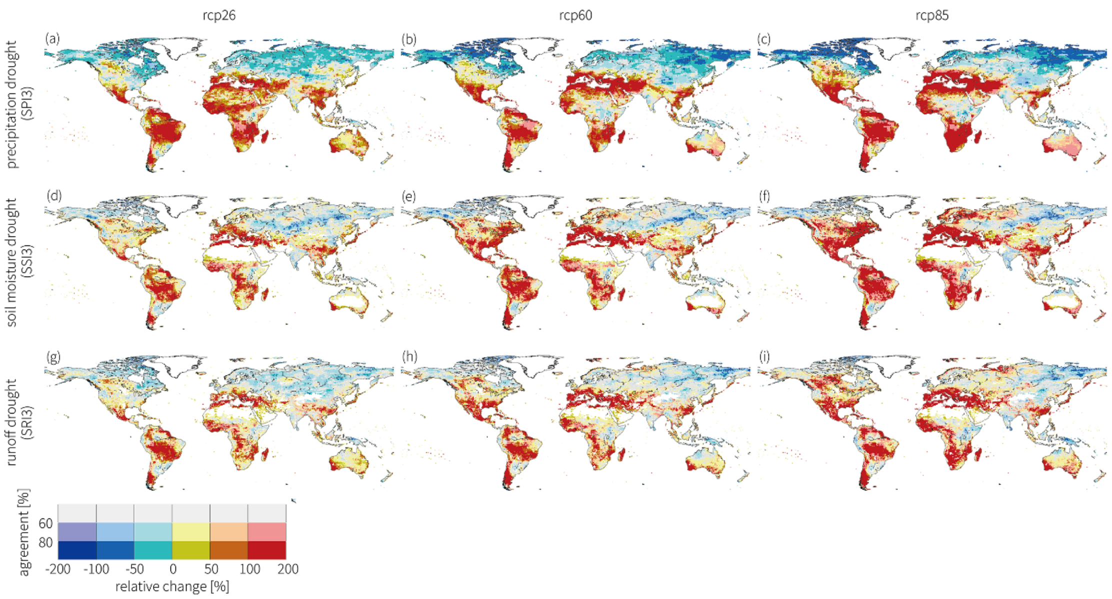

Figure 1. Ensemble median of percent changes in the total drought months between the historical reference period (1861–1890) and the far-future period (2070–2099) for each drought type (row) and GHG concentration scenario (column). The results for the scale-3 cases are presented. The vertical axis of the 2D color bar is the ensemble member agreement in the sign of change, and a grid is colored in gray in cases where the agreement is less than 60%. The same figure with only statistically significant changes for the mid-future (2035–2064) and far-future can be found in supplementary figure S1.

3.2. Disagreement in the sign of changes between drought definitions

Not only the magnitude of changes, but the sign of increases or decreases can differ when different drought definitions are applied, which can be critical in climate change impact assessments. To better understand where differences in drought definitions would result in inconsistent signs of warming impacts, we explicitly illustrated agreement and disagreement in the sign of change between different scales or drought categories, based on the ensemble median.

Concerning the difference in accumulation temporal scales, most disagreements accompanied an increase in the drought frequency for a shorter scale and a decrease for a longer scale, indicating hydrological intensification in such regions (figure 2). Broadly, regions with disagreement were similar among combinations of scales, and shorter (longer) scales showed a larger spatial extent of an increase (a decrease) in drought months than longer (shorter) scales. This applied to all drought categories, scenarios, and future periods (supplementary figures S4 and S5). Importantly, these changes with opposing signs were not necessarily small. In particular, concerning most disagreement between scale-3 and either of scale-6 or -12, increases in scale-3 and decreases in a longer scale were not small (>10%). On the other hand, the spatial distribution of disagreement due to scales can vary among drought categories, scenarios, and periods.

In terms of disagreement due to drought categories, figures 3(a)–(c) show the spatial distribution of inconsistent signs of changes in each combination of categories for scale-3 in the far-future under RCP8.5. Figures 3(e)–(g) present ten regions that had the largest total area fraction of disagreement. The regional definition is derived from AR6 WG I (Iturbide *et al* 2020). Overall, areas with disagreement in signs between precipitation drought and the other two drought types were analogous. The frequency of precipitation drought is likely to decrease over a large extent in northern high latitudes and Eastern Canada as well as parts of Asia and East Africa, but those of soil moisture and runoff drought were projected to increase. These disagreements dominantly result from inconsistent changes during the summer season (supplementary figures S6 and S7). Conversely, a decrease in soil moisture or runoff drought frequency despite an increased precipitation drought frequency was found in several localized areas, such as in Argentina, India, Northern Australia, and Northeast Africa. Regarding the combination of precipitation and soil moisture drought, 18% (4%) of the global land area showed disagreement via a decrease in precipitation drought and an increase in soil moisture drought (opposite) (figures 3(a) and (e)). Notably, most of these disagreements also resulted from changes that were not small (>10%). Specifically, disagreements in Eastern Canada and regions from North Europe to the middle of the Russian-Arctic involve even larger opposite changes (>50%). The member agreement in

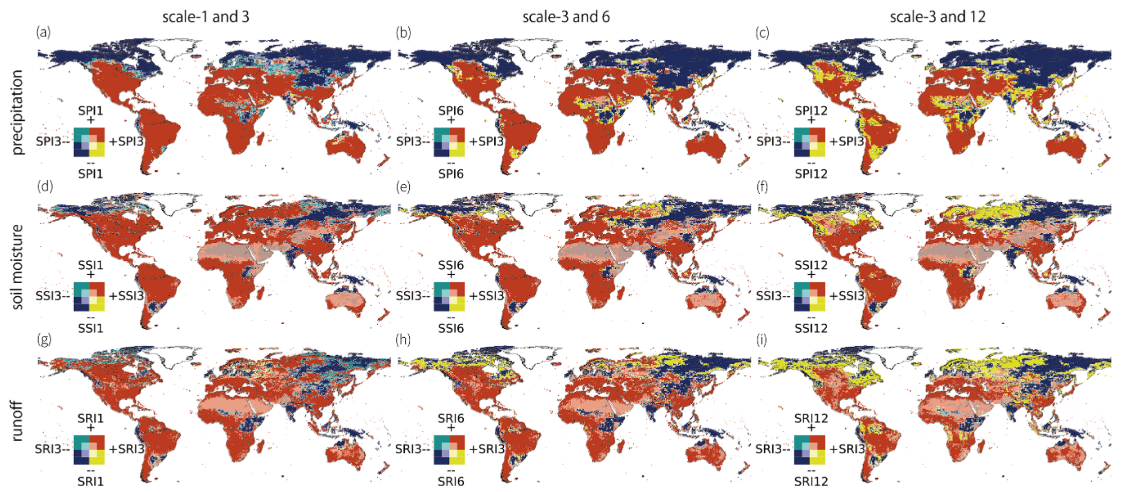

Figure 2. Agreement and disagreement in the signs of changes between different temporal scales of accumulation periods for each standardized drought index in the far-future period under RCP8.5. Drought types are meteorological, agricultural and hydrological drought in the top, middle and bottom rows, respectively. The global maps are presented for various combinations between the three months scale (scale-3) and another scale: scale-1 (left), scale-6 (center), and scale-12 (right). Green and yellow indicate disagreement between two scales. For instance, in the case of green (yellow), the drought frequency is projected to decrease (increase) in the scale-3 case but to increase (decrease) in another scale. For red and blue, the two drought types show a consistent sign of the change. The grid color is pale when percent changes are less than 10% in both or either of scales. The same information but for RCP2.6 far-future and RCP8.5 mid-future are presented in supplementary figures S4 and S5.

the sign of change tended to be high in these regions (figure 1).

Signs of change between soil moisture and runoff drought can also differ (figures 3(c) and (g)). In northwest North America, East Europe, West Siberia, and the middle and eastern Russian-Arctic; runoff drought is anticipated to increase, although soil moisture drought is projected to decrease. The opposite can be found in some regions, such as parts of East Central and Southeast Asia, North Europe, East Africa, and East Canada.

However, the abovementioned regions showing opposite signs between drought categories were not necessarily consistent when comparing different RCPs, periods, and scales, although regions with a consistent significant increase between drought categories shared similarity (supplementary figures S8–S10).

3.3. The relative importance of the issue of drought definition

Assuming that the diversity of drought definitions is a source of variance in synthesizing future drought estimates, this study evaluated the relative importance of the definition issue. Importantly, we found that the relative contribution of temporal scale parameters was insignificant compared to drought category, scenario, and model uncertainties (supplementary figure S11). Therefore, even though drought categories and scales were separately addressed in the previous section, we decomposed the variance into scenario, GCM, and GWM uncertainties, and drought definition, including drought definition and scales.

The overall variance in the projected changes in drought frequency is presented in the form of the fraction of unbiased standard deviation to the ensemble median in figure 4(a), highlighting regions where the spread among projections was critical in this drought assessment. Regions with larger changes (e.g. >50%) presented in figure 1 show a smaller fraction of uncertainty, but the relative standard deviation could be comparable or even larger than the median change in many parts of the world. Member agreement in the sign of change tended to be low, or disagreement due to scale or drought categories was observed in these regions (figures 1–3).

Using four-way ANOVA, we estimated the relative importance of each source of variance and investigated their spatial distribution (figure 4(b), supplementary figure S12). In general, models were the most dominant sources of uncertainty. GCMs showed a high contribution to the overall uncertainty over a large spatial extent. Regionally, more than 40% of the variance was attributed to GCMs in parts of the tropical or subtropical monsoon regions in North America, northern South America, central and southern Africa, and Southeast Asia. However, the relative standard deviation was small in these regions. Similarly, the relatively high contribution of GWMs covered a large spatial extent but with less heterogeneity than the GCM-dominant regions. The contribution of scenarios was spatially limited. The results with large contributions of models and a small contribution from scenarios are consistent with the findings of preceding studies (Orlowsky and Seneviratne 2013, Lu et al 2019).

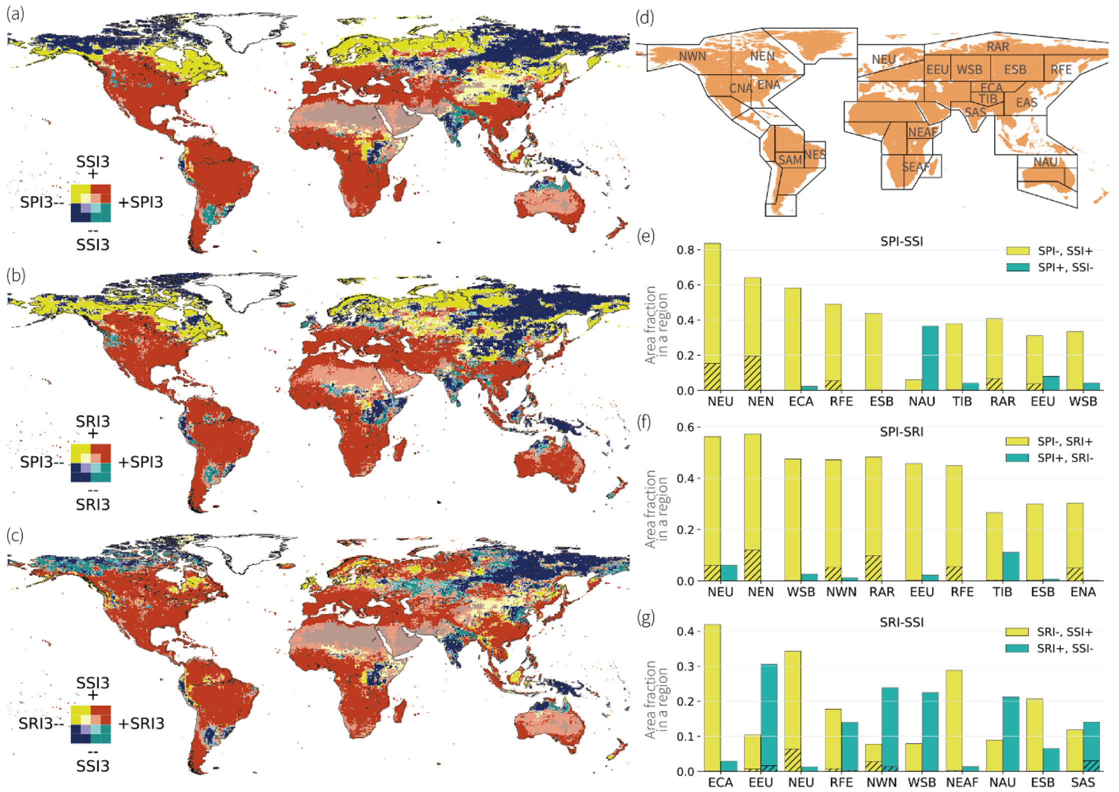

Figure 3. Agreement and disagreement in the signs of changes between different drought types in the far-future period under RCP8.5. The results for the scale-3 cases are presented. The global maps show all combinations among three drought types: (a) precipitation and soil moisture droughts, (b) precipitation and runoff droughts and (c) soil moisture and runoff droughts. Green and yellow indicate disagreement between two drought indices. For example, yellow in figure (a) indicates a decrease in precipitation drought but an increase in soil moisture drought. In red and blue areas, the two drought types show a consistent sign of the change. The grid color is pale when the percent changes are less than 10% in both or either of the variables. The same figures but for other scenarios and another period are presented in supplementary figures S8–S10. Figure (d) shows the reference region category defined by Iturbide *et al* (2020). Figures (e)–(g) present area fractions with the disagreement in each region, corresponding figures (a)–(c), respectively. The regions were sorted by the total disagreement area fraction for each drought type, and the top ten regions are shown. The hatched part in a bar presents the area fraction of regions where changes in both of two drought categories were statistically significant and the agreement in the sign of changes among ensemble members were greater than 60%. The rest of the non-hatched section indicates the area fraction of regions where changes in either or both two drought types were statistically insignificant and/or ensemble member agreement in the sign of change were less than 60% (ECA: East Central Asia, EEU: East Europe, ENA: East North America, ESB: East Siberia, NAU: North Australia, NEAF: North-east Africa, NEN: North-east North America, NEU: North Europe, NWN: North-west North America, RAR: Russian-Arctic, RFE: Russian Far-East, SAS: South Asia, TIB: Tibetan-Plateau, WSB: West Siberia).

In terms of the drought definition, its contribution to the overall variance was relatively high in parts of the northern high latitudes where different drought definitions showed disagreement in the sign of change. In particular, eastern North America showed the most significant contribution from the drought definition over a large spatial extent, followed by the west coast of North America and Central and North Europe. Importantly, the standard deviation was greater than the median change in these regions (figure 4(a)). The independent contribution rate of the drought definition in regions with disagreement between, for example, precipitation and soil moisture drought was 11% on average, while it exceeded 50% regionally.

The results also show the substantial contribution of interaction terms. In particular, interactions including GWMs and drought definitions constituted the majority of the uncertainty in many parts of the world. Their 1st-order interaction was important in regions ranging from northern Africa to south Asia, including regions exhibiting high uncertainties, and polar regions in North America and central-northern Asia (figure 4(b)). This was likely due to the ensemble spread in soil moisture and runoff simulations from GWM uncertainty. Although the 3rd-order interaction term constituted a large fraction of the uncertainty (>80%) in several regions, the relative standard deviation tended to be low in these cases (supplementary figure S12).

The primary factor among the four factors in the far-future is presented in figure 4(c) (the same figure for the mid-future is presented in supplementary figure S13). It was determined by the total contribution rate of each factor from the main to the 3rd-order interaction relevant. In the far-future period, for over 45%, 37%, and 17% of the global land area, the variance was dominantly attributed to the GCMs,

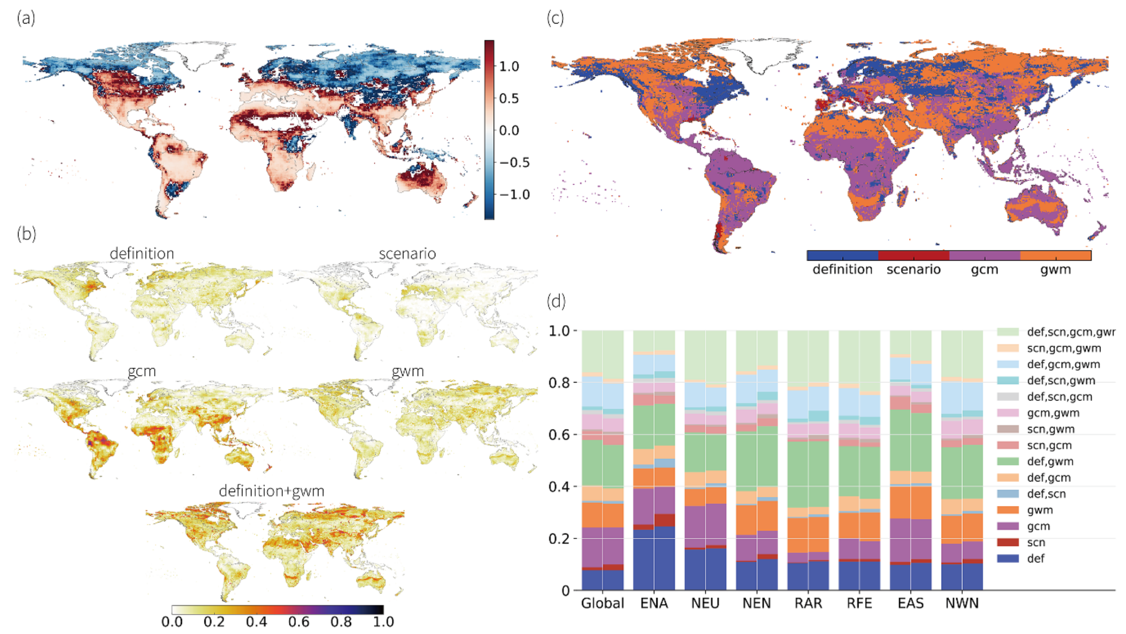

Figure 4. The fraction of standard deviation to median of percent changes (a), contribution rate of each factor in maps (b), dominant source of variance among the main factors (c), and a stacked bar graphs showing relative contribution rates (d). (b) shows the spatial distribution of the relative contribution of the main factors: drought definition, scenario, GCMs, and GWMs, and the map at the bottom shows the 1st-order interaction term between GWMs and drought definition. The stacked bar graph presents the relative importance of each term (supplementary equation (4)), and left and right bars for a region represent the mid- and far-future, respectively. The labels def, scn, gcm, gwm correspond to drought definition, scenario, GCM and GWM uncertainties. Location of regions are presented in figure 3(d) (ENA: East North America, NEU: North Europe, NEN: North-east North America, RAR: Russian-Arctic, RFE: Russian Far-East, EAS: East Asia, NWN: North-west North America). All results are for the far-future period.

GWMs, and drought definitions, respectively. For regions with a relative standard deviation greater than 1, these values were 40%, 39%, and 21% in the same order. As a result, the drought definition, including its interactions, constituted the dominant source of variance over a large spatial extent, specifically in the eastern part and northwest coastline in North America, Central, North, and East Europe, and West Siberia. Therefore, it can be considered that the highlighted uncertainties in the regions in figure 4(a) primarily result from the different drought definitions. In these regions, the member agreement tended to be high in precipitation and soil moisture drought, but their signs were opposite, while the member agreement was low in runoff drought (figure 1).

Considering the spatial extent and magnitude of the relative standard deviation, figure 4(d) summarizes the relative importance of the sources of variance on a global scale and for the top seven AR6 regions that exhibit a high contribution rate of drought definition (supplementary equation (4)). Globally, 35% of the variance for the far future was derived from the main factors (hereafter, main factor variance), and 45%, 29%, and 21% of the main factor variance stemmed from the GCMs, GWMs, and drought definitions, respectively. Even though model-related uncertainty was dominant, this number demonstrates that differences among drought definitions have the potential to result in not a small fraction of the variance when comparing drought assessments. At the sub-continental scale, Eastern North America and Northern Europe showed the largest relative importance of the drought definition among all AR6 regions. The relative importance of the three factors was comparable between the mid- and far-future, but that of the scenario grew over time, especially in regions in Europe and South and North America.

4. Discussion

4.1. An application to wheat and maize production regions and seasons

For a specific interest, the relative importance of uncertainty sources can provide different perspectives compared to the results in the previous section. Cook *et al* (2020) conclude that uncertainty depends heavily on the region and season as well as indicators being considered. Hence, this section presents a case study on wheat and maize production to give a more practical interest. Even though soil moisture drought is supposed to be of the primary interest for the agricultural sector, SPI and SRI are also often used in relation to crop production (e.g., Mishra and Cherkauer 2010, Kim *et al* 2019). We examined the change in drought frequency during their growing seasons and

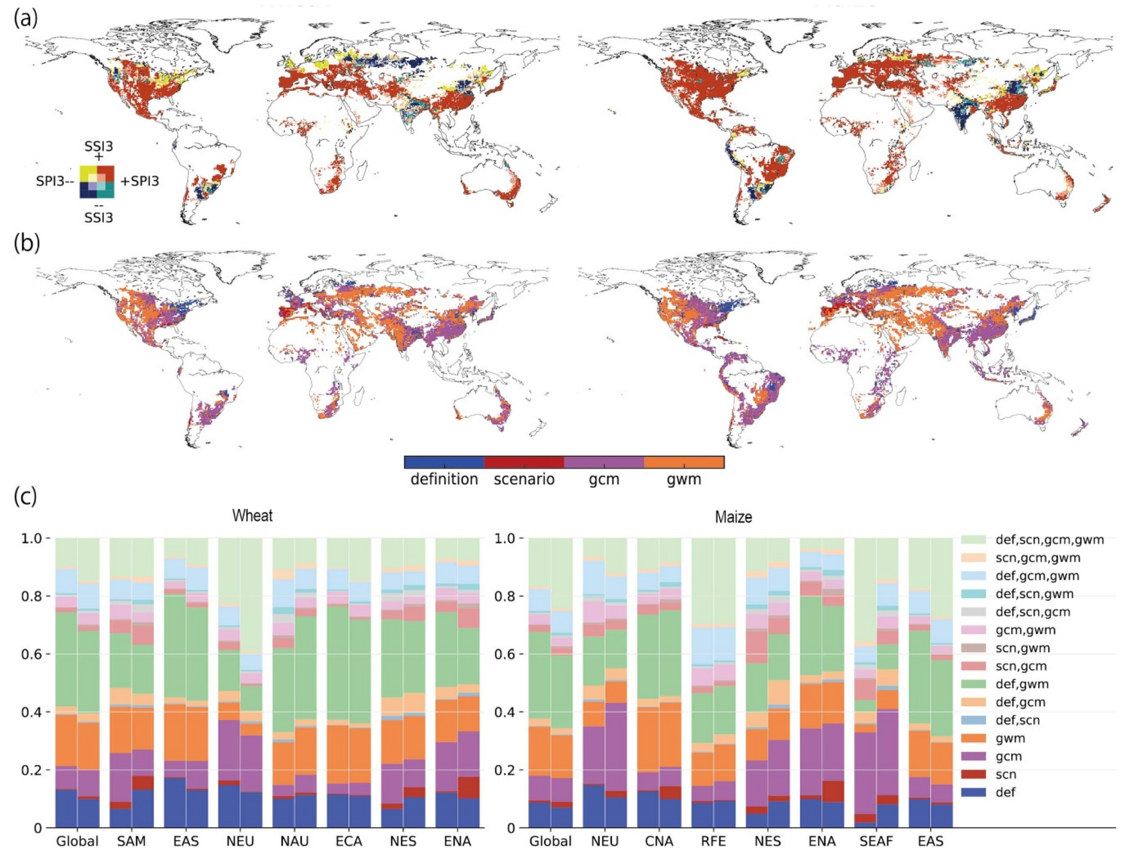

Figure 5. Results for wheat (left) and maize (right) production areas and seasons regarding the scale-3 case; (a) agreement and disagreement in the sign of changes between SPI and SSI in far-future under RCP8.5. The grid color is pale when the percent changes are less than 10% in both or either of scales. (b) Dominant source of variance among the main factors. (c) The relative importance of each source of variance on a global scale and for top seven AR6 regions that exhibit high contribution rate of drought definition (supplementary equation (4)). The labels def, scn, gcm, gwm correspond to drought definition, scenario, GCM and GWM uncertainties. Drought months are counted only for crop-specific growing months. Location of regions are presented in figure 3(d) (CNA: Central North America, EAS: East Asia, ENA: East North America, NEU: North Europe, NAU: North Australia, ECA: Eastern Central Asia, NES: North-eastern South America, RFE: Russian Far-East, SAM: South-American-Monsoon, SEAF: South-eastern Africa).

applied the same analyses presented above. Because the three-month scale accumulation is often applied in this context and the contribution of scales to variance was found to be much smaller than drought categories, this section focuses on the scale-3 case. For simplicity, the crop area and calendar were fixed to their historical conditions based on MIRCA2000 (Portmann *et al* 2010).

Disagreements in the signs of change among the drought categories were seen over some major wheat- and maize-growing regions. Figure 5(a) depicts the disagreement between SPI and SSI in the far future for RCP8.5. Importantly, areas with opposing trends spatially corresponded well to major wheat production regions (e.g. eastern China, northern India to Pakistan, parts of Europe, and northeast USA). Precipitation was projected to increase in these regions, but soil was expected to become drier due to increased evapotranspiration. Thus, drought categories need to be carefully considered for such regions in assessing future drought changes. In general, most of the major wheat production areas are anticipated to experience more agricultural drought.

In terms of maize production regions compared to that of wheat, a comparatively different spatial distribution of disagreement was observed due to different growing seasons. Unlike wheat, the projected increase in the drought frequency during the maize production season was consistent between SPI and SSI in eastern North America and Europe. Overall, agricultural drought was projected to increase in most maize-producing regions, apart from parts of India, eastern China, Argentina, and the eastern coastline of northern South America.

The ANOVA results indicate that most wheat and maize production regions were primarily subjected to model uncertainties. Even in regions with the disagreement in the median change in drought frequency, GWMs tended to be the dominant source of variance in Asia, and GCMs tended to be the dominant factor in North and South America and East Europe. Scenario uncertainty played an important role in Europe, especially for maize production. Nonetheless, drought categories can also be a critical source of variance for wheat and maize production in specific regions, such as eastern North America and several areas in Europe where crop production is large, and some eastern parts of East Asia and Brazil for maize (figure 5(b)).

The independent relative importance of the drought category was larger in regions in Asia and North America among AR6 regions (figures 5(b) and (c)). Its global values were 9% and 7% in the far-future for wheat and maize, nearly equal to the result in figure 4(d). Nonetheless, the independent relative importance of the drought category was lower on all continents compared with the results in figure 4(d), except wheat in Asia. Instead, the contribution of scenario uncertainty was significant for the far-future, particularly in Europe and South America for wheat and Europe for maize. Furthermore, the independent relative importance of GWMs was larger regarding this topic. For instance, 19% of uncertainty was singularly attributed to GWMs in the mid-future for wheat, while it was 10% in figure 4(d). Without any exceptions, GWMs, followed by GCMs, were the overall dominant sources of uncertainty in wheat- and maize-growing regions on each continent. On the other hand, if the interaction terms are considered, the largest fraction of overall variance stemmed from the interaction terms that include drought categories and GWMs, especially from their 1st-order term. This implies that better land surface processes and proper drought definitions could play crucial roles in reducing the overall drought projection variance for wheat and maize production areas.

4.2. Limitations of this study

This study first provides a quantitative and spatial assessment of the relative role of drought categories and scales in the variance of drought assessment compared to other uncertainty sources; however, certain limitations could be addressed in future studies. First, the drought definition issue inherently includes the selection of drought indices within a drought category. This study examined only three standardized drought indices that are widely used for each drought category. Even though there are more drought indices, such as the standardized precipitation-evapotranspiration index (Vicente-Serrano *et al* 2010), Palmer drought severity index (Wells *et al* 2004), and various threshold methods (Prudhomme *et al* 2014), we applied indices that are straightforward and take advantage of ISIMIP2b off-line simulations. Second, the intensity, number of events, and duration of drought were not considered in this study, which are also important aspects of drought in addition to frequency. Third, a reference base period defining normal conditions is crucial because drought indices are relative terms. Fourth, a more in-depth seasonal scale assessments are important. For instance, a shift in seasonal hydrological regimes in a warmer world may need further investigation to better understand the processes behind such changes. Fifth, regarding the uncertainty analysis, including additional GCMs could enable a more robust discussion because this study relied on only four bias-corrected GCM projections used in ISIMIP2b simulations. Although a bias-corrected forcing dataset and multi-model offline hydrological simulations at a higher spatial resolution under a consistent setup are advantageous for this impact assessment of climate change, the small number of GCM samples could be insufficient to cover the full range of uncertainties projected by the entire CMIP5 ensemble (Frieler *et al* 2017, Ito *et al* 2020). We expect that future studies would refine our results and provide a more comprehensive and robust assessment.

5. Conclusion

Using a multi-model and -scenario dataset, this study evaluated changes in the drought frequency of three drought categories (meteorological, agricultural, and hydrological droughts) by considering four accumulation temporal scales to investigate where and to what extent differences among drought definitions could result in pronounced variance compared with other sources of uncertainty.

While the models were the dominant source of uncertainty over 82% of the global land area, our results quantitatively show that differences among drought definitions, particularly concerning drought categories, have the potential to be the dominant source of variance across northern high-latitude regions, especially in eastern North America and northern Europe. The drought definition was the dominant source of uncertainty for over 17% of the global land area. Furthermore, the ANOVA results show that 21% of the main factor uncertainty, which corresponds to 7% of the total uncertainty, in the far-future was independently attributed to the drought definition at a global scale. On the other hand, the GCMs were the dominant source of uncertainty and contributed to 45% of the main factor uncertainty in the global average, followed by the GWMs. The spatial distribution of the dominant source of uncertainty indicates that, especially for arid and cold regions, improvement of the terrestrial hydrological processes in GWMs are essential to reduce uncertainty.

Although the uncertainty was dominantly attributed to climate and impact models and the contribution of the drought definition was rather localized, our analysis demonstrated that generalizing future drought changes covering multiple drought categories introduces difficulties that lead to additional uncertainty. In other words, we could avoid this uncertainty if each drought category is specifically discussed. We do not suggest a universal integrated drought index. The results underscore the importance of a distinction among drought definitions and the need for a better understanding of similarities and differences among the definitions in the context of climate change. The word 'drought' is often ambiguously used, but each drought category represents specific hydroclimatic processes; hence, inherently, different drought categories consider different phenomena. Considering that the signs of warming impacts could be opposite depending on drought definitions, the ambiguity could lead to misunderstanding. The results imply that separately describing each drought category should be an essential approach to deliver the results of drought assessments with improved confidence levels. Compared to the previous IPCC reports, Chapter 11.6 in AR6 WGI discusses each drought category more explicitly in a sub-section of each drought category, presenting a more lucid assessment. This implies the importance of making a clear distinction among drought categories of interest. Particular attention should be paid to drought definition when interpreting drought assessments.

Data availability statement

The model results are freely available from the ISIMIP project portal (www.isimip.org/outputdata/). The processed data used to generate the figures in the main text are available from the authors on reasonable request and following data restrictions from the sources.

Code availability

Standardized drought indices were calculated by a Python library provided by National Oceanic and Atmospheric Administration's National Centers for Environmental Information (NCEI), National Integrated Drought Information System (NIDIS) (https://github.com/monocongo/climate_indices). All processed data and figures were also generated using Python. The relevant portions of the Python scripts used to process the results and develop the graphic presentation are available at https://github.com/yusuke61/drought_definition_issue.

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