Response to Referee 1

We thank the referee for his/her in-depth review and constructive comments. The referee raises some important points (in bold), and we address each of these in a point-by-point fashion below. See the second Supplement for a revised version of the manuscript.

Main issues:

The authors chose for their analyses eight accumulation periods that represent different timescales (1, 2, 3, 6, 9, 12, 24 and 36 months for sub-seasonal, seasonal and annual timescales). These accumulation periods are similar to those that are often used, but still arbitrary. For example, they could have chosen only 1, 3, 6, 12 and 24 months for the same reasons. For the determination of propagation timescales this choice is probably of minor relevance, however, for the applied statistical tests I think it can have quite some impact. The tests used in this study are designed for variables on the interval scale (apart from spearman's rho) but the variables are on ordinal scale. The authors are aware of that problem and state they "assume that the difference between accumulation periods of 12 and 24 months (. . .) to be equivalent to the difference between 1 and 2 months" (p.5, l.5ff). Nevertheless, it is still very relevant to check whether there is an influence of the arbitrary choice of accumulation periods and the related assumption on the results of the statistical tests. Additionally, it needs a strong rationale for using tests designed for interval scaled variables instead of tests appropriate for ordinal scaled variables (e.g. the chi-squared test of independence).

First, we will discuss the choice for certain statistical tests, then we will investigate the sensitivity of the results and conclusions to the (number of) accumulation periods.

As the referee indicated, there are statistical tests that have been designed for ordinal variables, such as Chi-squared and Cramer's V (effect size metric). In the preparation of this study we considered using these metrics and calculated their results. The outcome of Chi-squared, for example, was that difference in SPI-n by climate type is highly significant ($p < 0.001$) for all drought types and seasons. However, an important disadvantage of using Chi-squared and other metrics for ordinal data is that these metrics treat ordinal variables as categorical variables. This means that the relationships between SPI-n are ignored. In the end we chose ANOVA tests because we believe it is important to take the relationship between SPI-n into account and because the SPI accumulation periods are nearly equidistant in log space. In the revised version of the manuscript, we include outcomes of the Chi-squared metric (P12 L1+6) and elaborate on the motivation for using ANOVA tests (P5 L17-21).

The sensitivity of the conclusions to the SPI accumulation periods is a good point. To address this, we recalculated the (significance of) the results using fewer SPI accumulation periods (1, 3, 6, 12 and 24 months, as suggested). As expected, changes to global patterns of SPI-n are minimal when fewer accumulation periods are used. This is shown for summer SPI-n in Figure R1, but is also true for winter SPI-n. In addition, outcomes of Chi-squared and ANOVA tests are still highly significant ($p < 0.001$). The pairwise comparisons using Tukey's honestly significant difference test show minor differences for runoff droughts. To be more specific, the difference in mean rank SPI-n between

tropical savanna and dry climates is no longer statistically significant in summer. In winter, the difference between tropical wet and dry climates is no longer statistically significant. Pairwise t-tests were used to test between summer and winter droughts, and the results for fewer accumulation periods were the same as with more accumulation periods. Therefore, the conclusions of this study are not affected by using fewer SPI accumulation periods. We summarize the results of this sensitivity test in the revised version of the manuscript (P14 L2-5).

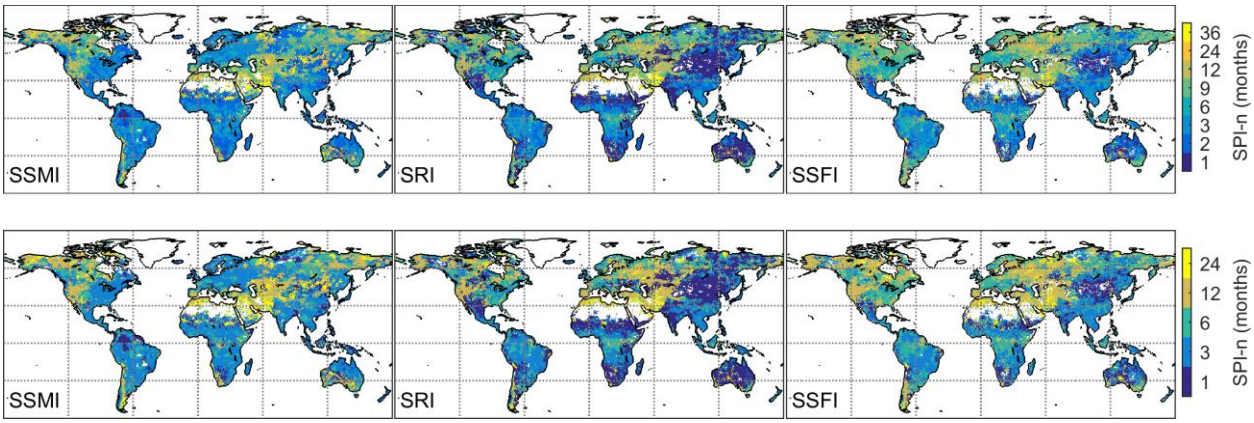

Figure R1. The SPI accumulation period (SPI-n) resulting in the highest correlations with model ensemble mean SSMI, SRI, and SSFI, for summer droughts using the original larger selection of accumulation periods (top) and a smaller selection of accumulation periods (bottom). Pixels where those correlations are not statistically significant ($p < 0.05$) are masked.

The second main issue is about the way the model ensemble mean is calculated: "The model ensemble mean was calculated as the average of the SIs" (p.6, l.29). A very important reason for using standardised indices is to ensure that all time series have the same distribution and are directly comparable (see e.g. Bloomfield and Marchant, 2013; Kumar et al., 2016). Averaging two or more timeseries, that have a standard normal distribution, will lead to a timeseries which distribution has a smaller standard deviation that might favour certain (higher) SPI-n. Moreover, the comparison with the results from the original model time series as it is carried out in chapter 4.3 is not really "fair" anymore, since time series are not directly comparable. The correct way is to average the raw model outputs first and standardize afterwards all seven time series plus the model ensemble mean.

We agree that we have deviated from the usual way of calculating the ensemble mean by averaging SI time series rather than the original model time series. Our motivation for averaging SI time series was that we did not want one or two models with high soil moisture/discharge (variability) to dominate the overall signal. For discharge we expected this to be less of an issue than soil moisture, where total storage (and variability) varies considerably between models (see for example Figure 6 of the manuscript). In addition, though standardization is an important reason for using SIs, we do not use the time series directly in the analyses. Even in the evaluation section, we compare SPI-n and not the time series themselves.

Nevertheless, we recalculated ensemble mean SPI-n using the approach of averaging of the original model time series. Overall, results are similar to when the ensemble mean was based on averaging SI time series: SPI-n does not change in 60-67% of all pixels, and changes by a maximum of 1 rank SPI-n in 80-85% of all pixels (Figure R2). For all climates and seasons, the mean rank SPI-n changes by less than 1. A closer examination of the pixels showing a change in SPI-n shows that soil moisture droughts are most affected by changing the ensemble mean calculation method. For these droughts, SPI-n tends to be higher when original model time series rather than SI time series are averaged. This is especially the case for summer droughts in tropical wet, dry and polar climates.

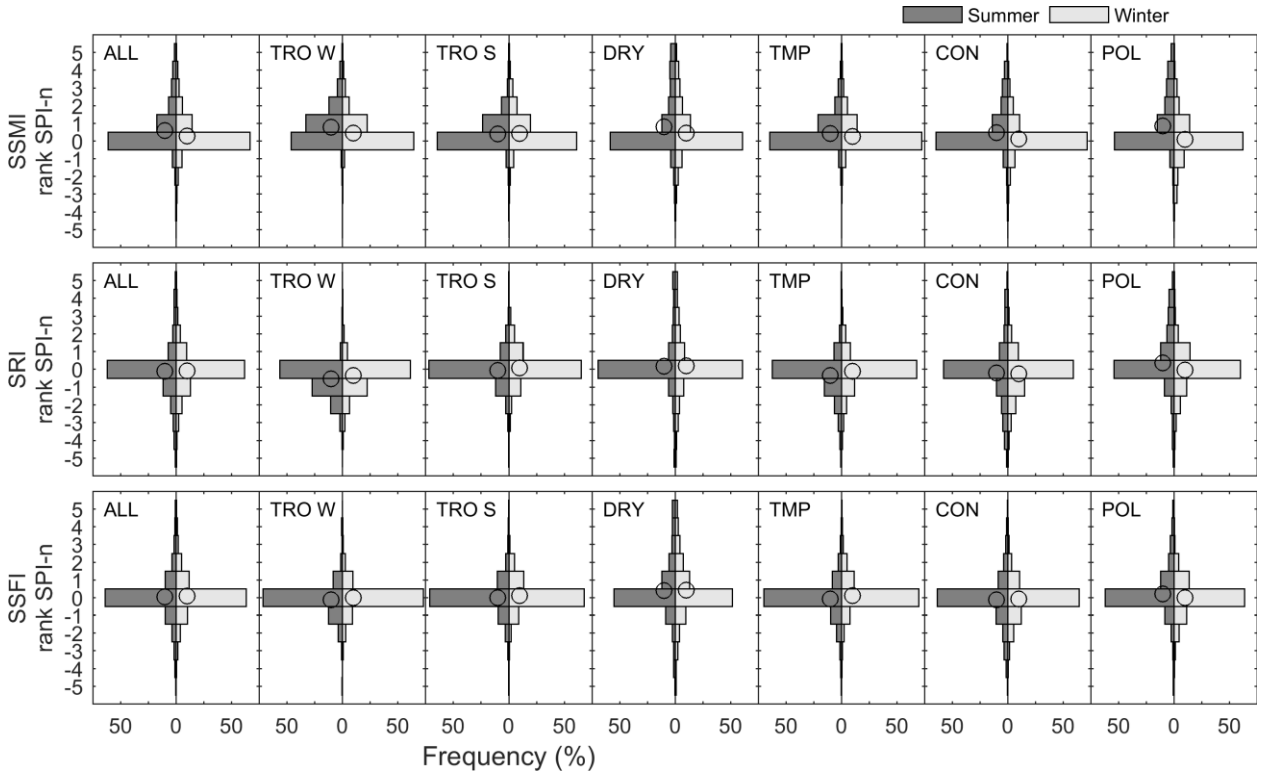

Figure R2. Histograms of the change in rank SPI-n when the ensemble mean is calculated as the average of the original model time series compared to when the SI time series are averaged. Changes in rank SPI-n are shown by climate type, and for summer and winter droughts in SSMI, SRI, and SSFI. Circles represent the mean change in rank SPI-n per climate type and season.

To further investigate the somewhat higher SPI-n for soil moisture droughts, we studied a pixel with a tropical wet climate located in central Africa (Figure R3). ORCHIDEE and SURFEX-TRIP, the models with the highest average soil moisture conditions (largely due to a deeper definition of the root zone), have a much higher soil moisture variability than the other models. The SI time series of these models are also very different from those of the other models. For example, the drought between 2004 and 2007 is much more pronounced in ORCHIDEE and SURFEX-TRIP, and the time series are smoother. As a result of the higher soil moisture variability, SURFEX-TRIP and ORCHIDEE have a larger impact on the average of the original model time series (EnsMean 2), and thus also in the resulting SI time series. Averaging SI time series (EnsMean 1) is a better representation of the 'average' behavior within the model ensemble.

The results shown in Figure R3 are representative of other model pixels where changing the ensemble mean calculation method results in changes of more than 3 rank SPI-n. The underlying cause of these large differences is that the models use different definitions for root-zone soil moisture. In some models this is a fixed depth, in others this varies with vegetation type. Ideally, the root-zone soil moisture time series could be normalized between 0 and the maximum soil moisture content before further analyses. However, the maximum soil moisture content is not always easy to define because vegetation types and rooting depths can vary within pixels.

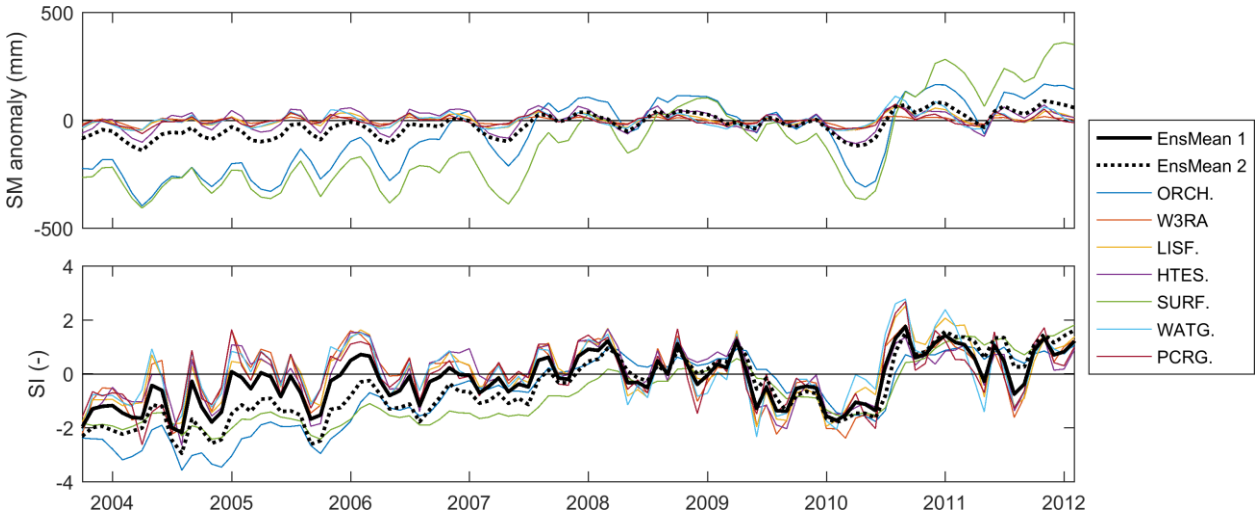

Figure R3. Time series of soil moisture content relative to the multi-year mean (top) and SSMI (bottom) for each of the individual models and two methods of calculating the ensemble mean. EnsMean 1 is based on averaging model SI time series, EnsMean 2 is based on averaging the original model time series.

In summary, though changing the calculation of the ensemble mean can have a large impact on SPI-n for individual pixels, the main conclusions of this study are not sensitive to the ensemble mean calculation method. This is probably because even though averaging does result in fewer extreme values in the ensemble mean, SPI-n are based on correlations between SI time series, which are not as sensitive as other metrics to a narrower range in values. Since the results are similar overall and due to the results of the soil moisture averaging analysis as shown in Figure R3, we have decided to still calculate the model ensemble based on SI time series. However, we have added a statement clarifying why we chose a non-standard method to calculate the ensemble mean (P7 L22-29 and Fig. S1 in the revised manuscript), and that the main conclusions of this study are not impacted by this choice (P14 L5-9).

Finally, the authors use an explanatory analysis to identify relevant model characteristics causing differences in drought propagation timescale (p.15f). They are aware of the difficulties using only seven models for that and the problem of collinearity between the groups. In fact, these limitations inhibit any useful result. For example, the factors GHM/LSM and (no)reservoir are highly correlated. Based on Table 1, it is only the model W3RA that is classified into another group. That means, in a study without this model, the groups would have been identical, similar to what is reported about the

snow scheme. Accordingly, the graphs in Figure 7 of the two groups have a very similar shape. The authors wonder about the reason for the high influence of reservoirs on soil moisture (p.16, l.12), but the real problem is, that both factors (GHM/LSM and (no)reservoirs) represent the combined effect of (no) reservoirs, GHM/LSM, snow scheme and probably several other relevant model structures. As it is not possible to relate the differences of the groups to one model structure we cannot learn much from this analysis.

We completely agree that we cannot attribute the observed differences to investigated model structures and parameterizations. We attempted to make it clear that while we cannot do so, we present an initial exploration only. For example, we think it is important to note the large differences between LSMs and GHMs, even though we cannot pinpoint the exact mechanism(s) responsible for that difference. This exploratory nature of this analysis has been made clearer in the results section (P16 L19-21) and in the conclusion (P21 L25-30).

Our paragraph concerning the simulation of reservoirs was poorly phrased. We included this factor because previous studies have shown that it plays a role in hydrological drought propagation. We agree that reservoirs are not likely to play a role in soil moisture droughts, and therefore by including it we intended to warn that apparent differences can be misleading. In the revised manuscript, we have removed this factor from the effect size figure (Figure 7 in the manuscript). In the text, we instead refer to previous studies that investigated reservoirs and hydrological drought and explain that this distinction is not useful in our case due to the high similarity with grouping by model type (P18 L3-7).

Other points the authors might want to look at: In the introduction the authors acknowledge that an important component of drought propagation is the time lag (p.2, l.13ff). However, time lags are not considered in the analysis but listed to be important for future research (p.19, l.16). Including an analysis of time lags which also might differ for the models would increase the relevance of this study. If lags are not included, there should be at least a rationale for excluding them despite their relevance.

Lag is indeed an important characteristic of drought propagation. We have recalculated SPI-n using SPI with different accumulation periods as well as lags up to 12 months for the model ensemble mean. Results show that, as expected, taking lag into account has a larger impact on winter drought propagation than on summer drought propagation. In summer, the best drought propagation result has a lag of 0 months in around 70 % of the pixels (Figure R4). In winter, 0-month lags are still the most common, but account for only about 40 % of the pixels. Shorter lags (1–3 months) are more prevalent than longer lags (8–12 months).

The frequent occurrence of 0-month lags for summer drought propagation means that SPI-n also remains unchanged in a majority of pixels. However, even for winter droughts SPI-n are not affected by taking lags into account in about 60 % of the pixels. This means that for about 20 % of pixels, taking lag into account does not change SPI-n, but does improve the correlation between SPI-n and the winter drought SI of interest. Changes in SPI-n in both seasons tend to be small, with changes in rank SPI-n larger than 2 occurring in less than 10 % of pixels. Positive changes in SPI-n are more

frequent than negative changes, meaning that overall taking lag into account leads to longer SPI-n. This is the opposite of what we hypothesized in the previous version of the manuscript. We had expected that lag would be especially important in areas with significant snow cover in winter, and that including lags would lead to lower SPI-n.

These results show that lag does play a role in drought propagation, though this is more so in winter than in summer. Even so, SPI-n are not very sensitive to whether lags are included in the analysis or not. We could add this figure to the supplementary material, but the Supplement is already large, containing seven figures. Since this was not one of the major comments, we suggest not adding this figure to the supplement. However, we leave the final decision to the referee and editor.

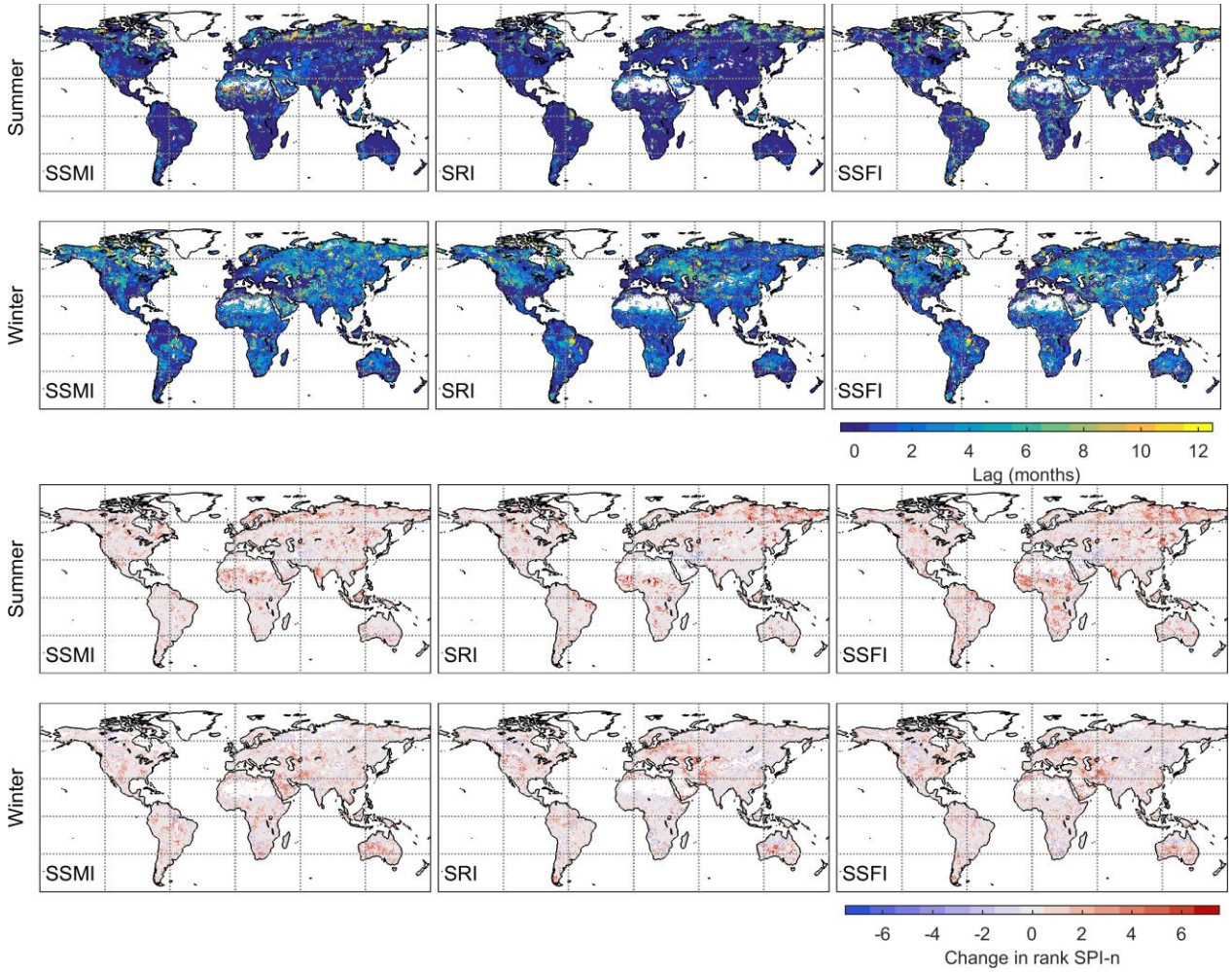

Figure R4. The SPI-n lag in months leading to the best correspondence with SSMI, SRI and SSFI for summer and winter droughts (top) and the change in rank SPI-n compared to when lags are not taken into account (bottom). Pixels where the correlations between lagged SPI-n and SI time series are not statistically significant ($p < 0.05$) have been masked.

In chapter 4.1 analyses of the "mean SPI-n" are presented (e.g. p.10, l.17; caption of Figure 3). For me it does not become clear, whether this is really the arithmetic mean of the SPI-n or rather the mean of

the ranks. For example in Figure 3: If there were the two accumulation periods of 1 and 36 months, is "mean SPI-n" (1+36)/2=18.5 or rather (1+6)/2=3.5? This is quite relevant for the plotted circles. If they are calculated as an arithmetic mean, it might be very hard to read the values from the plot due to the very non-linear y-axis.

This should indeed all be mean rank SPI-n. We have changed "mean SPI-n" to "mean rank SPI-n".

Moreover, it is important to report somewhere the 'sample size', i.e. the absolute number of cells which are not masked for the different climates and drought types. Otherwise it is for example hard to understand, that the t-test leads to significant different SPI-n means for winter and summer in runoff of TMP (Figure 3).

Agreed, we have added the number of pixels for each climate and drought type to the panels in Figure 3 of the revised manuscript.

On page 10, l.16 the authors describe the results of the ANOVA: "The means of SPI-n for winter hydrological droughts in continental and polar climates are not significantly different". Again, for me it is not clear whether the rank mean or the arithmetic mean is meant here. However, more important is the fact that it sounds like two categories were directly compared to each other. In this case, it would have been a t-test rather than an ANOVA what was used. Please clarify, which variables were used for the ANOVA and in which cases a t-test was used.

This should indeed be mean rank SPI-n, and the text has been revised to reflect this. An ANOVA test was used for the comparison over multiple groups. A statistically significant ANOVA test result was followed by Tukey's honestly significant difference tests to compare each pair of group means. This test is very similar to a t-test, but corrects for family-wise error rates. This correction is needed because the chance of making a type 1 error (false positive) increases when comparing multiple groups. The use of Tukey's tests has been added to the Methods section (P5 L21-23) and the Results section (P12 L2-4).

The stations used for the evaluation against observations are distributed very uneven (as the authors write on p.18, l.7). In Figure 8 it looks like there were very few to no stations in the climates polar and tropical wet. However, the authors state that "errors between models and observations are not related to climate". To enable the reader to comprehend this important finding, I think it is necessary to give more information on the number of stations per climate zone, the test used to reach this conclusion as well as the results of the test.

We agree that the link between GRDC stations and climate type is not clear. Therefore, we have included the stations in Figure 1 of the manuscript (the global map of Köppen Geiger classification used). In addition, we have included the number of stations falling within each class in the legend of the same figure.

The relationship between error in SPI-n and climate zone was based on ANOVA tests ($p < 0.05$). In the previous version of the manuscript, ANOVA results were not significant for any of the models. In

the revised version of the manuscript, however, some of the results have changed because we included an additional criteria for GRDC stations based on the agreement in upstream catchment area (see referee 2, comment 4). ANOVA results are now statistically significant for two out of seven models in summer and four models in winter. For the model ensemble mean, a statistically significant result is only found for summer droughts. The explanation of the test used and its results has been added to this section (P19 L7 – P20 L4, Fig. 9).

Response to referee C. Prudhomme

We would like to thank referee C. Prudhomme for the time and effort spent to review our manuscript and for her thorough and valuable comments. The feedback has helped us improve our manuscript. Below, we respond to each of the comments and indicate what changes have been made to the manuscript. The revised version of the manuscript has been included as a supplement.

The subject is very topical and relevant for publication in HESS. However, I regret that the analysis is done :

1) following climatic lenses (precipitation vs land surface; no analysis of propagation between the different land surface responses; summary/ discussion based on climatic regions without attempt to relate to soil/land surface/ bedrock/ catchment size etc. . . components). This is a shame and a more comprehensive analysis would be more valuable. Note that the title suggest 'effect of climate' but only precipitation (and not temperature/ evaporative losses) are considered, so it is not a full climate analysis that is undertaken ; 2) primarily on a multimodel mean (smoothing out extremely different behaviour; making extremely difficult a physical interpretation of results); 3) without justification of the choice of accumulations periods, which are arbitrary.

1. Undertake a full propagation analysis, by adding correlation between land surface components (soil moisture and runoff; soil moisture and discharge; runoff and discharge), and provide physically-based/ model structure/ parameterisation interpretation of the results. The analysis should also include at minimum catchment size, and if possible information on the land surface fields that should be available for all models.

> We have performed the suggested full propagation analysis by investigating drought propagation from soil moisture to both types of hydrological drought, and from runoff to streamflow drought. Similar to the analysis of propagation from meteorological to streamflow drought, the soil moisture and runoff to streamflow drought analyses used catchment-aggregated values of soil moisture and runoff. In summer, SSMI-1 had the best agreement with SRI and SSFI for most of world (Figure R5). Slightly higher SSMI-n are found in tropical regions, northern Europe, and parts of North America. In winter, longer SSMI-n up to (multi-)annual scales are more common, especially in continental climates. Drought propagation from runoff to streamflow droughts is generally quick in both seasons, with over 90 % of the pixels having a SRI-n less than or equal to 2 months. The similarity between runoff and streamflow drought propagation time scales is consistent with the meteorological drought propagation results (Figure 3 of the manuscript) and the difference in SPI-n (Figure 4 of the manuscript) for these drought types. Furthermore, the regions with positive differences between SPI-n in Figure 4 of the manuscript correspond more or less to the regions where SI-n are longer than 1 month in Figure R1 below, though the magnitudes are not necessarily equal. On the other hand, negative values in Figure 4 of the manuscript usually correspond to SI-n of one month. In these regions, drought propagation to runoff or streamflow is quicker than to soil moisture, which may be linked to a larger surface flow component in total runoff. This results in one-month SPI-n, though in fact this type of drought mechanism largely bypassing soil moisture

cannot be captured when analyzing propagation of soil moisture drought to hydrological drought. The full drought propagation analysis is presented in Figure S3 of the revised manuscript and described in an additional paragraph in Section 4.1 (P13 L14-24).

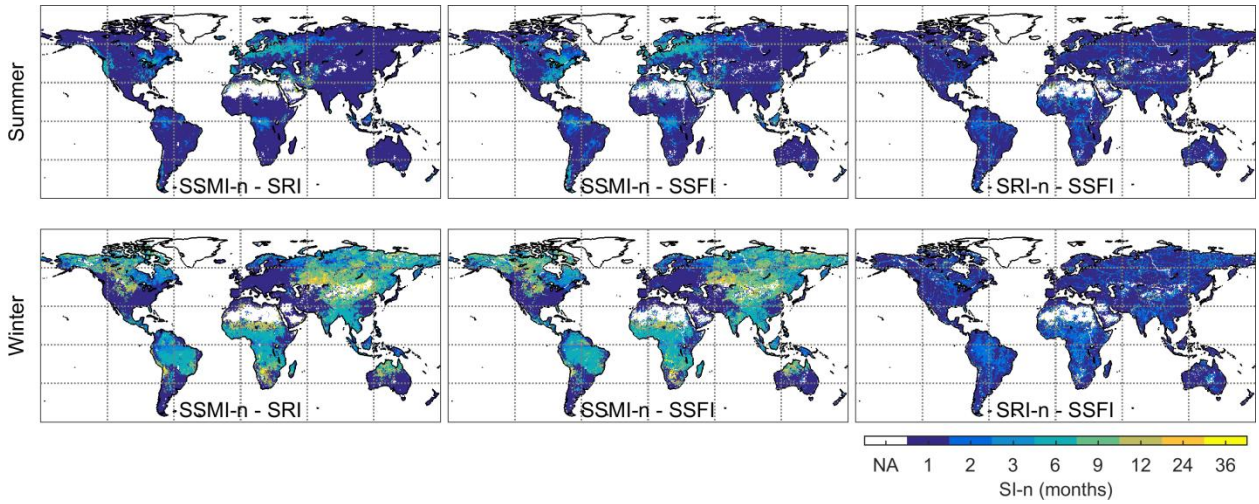

Figure R5. The SSMI and SRI accumulation period (SSMI-n or SRI-n) resulting in the highest correlations with model ensemble mean SRI and SSFI, for summer and winter droughts. Pixels where those correlations are not statistically significant ($p < 0.05$) are masked.

We fully agree that a physically based interpretation of differences between models would be very insightful, but is unfortunately not possible within eartH2Observe. Such an interpretation would require extensive experiments changing a large number of model structures and parameterizations, for example using Monte Carlo analyses. Even then, prescribing different sets of parameterizations is further complicated because choice of a certain parameterization is closely linked to the modeling system. This is also the reason the project did not prescribe a fixed set of static fields. We emphasize the need for comprehensive model structure and parameterization experiments in the Results (P16 L1-3) and Conclusion (P21 L28-30) sections of the revised manuscript.

The "effect of climate" in the title was meant to reflect how many of the analyses in our study focus on differences in drought propagation between Köppen-Geiger climate types. To make this clearer, we have changed the title to "The effect of climate **type** on timescales of drought propagation in an ensemble of global hydrological models".

2. Change the emphasis of the paper to individual models results, with the multi-model mean analysis presented last (if at all) with a justification of what it tells us. I am curious to know how different are the average SIs compared with individual models, and what mean SI represents physically. Understanding how the structure of the models influence drought propagation would be extremely valuable for future analysis. I fully agree with the point made by Referee #1 that there are strong collinearity between the different categories used to divide the models, and this should be considered in the interpretation of the results.

The ensemble mean result gives us an idea of the model consensus on drought propagation time scales globally and how these differ per climate type. We expect that the individual model results are indeed of interest to the respective modeling groups because they can compare their results to other models and the model ensemble mean, or model consensus. Therefore, we have added the model-specific results to the Supplementary Material (Figures S6 and S7). However, to make individual model results insightful for the larger community we would need to be able to attribute the observed differences to model structures and/or parameterizations. As explained previously in response to the first comment, this is not possible within the current experimental setup.

We agree that we cannot use the categories we used to divide the models to definitively identify the mechanisms underlying differences in SPI-n due to the large number of potential factors and limited number of models (or the collinearity between groups). Instead, we attempted an initial exploration of potential explanations for the differences between models based on our observations and previous work. We have rephrased the introduction to this analysis (P16 L19-21) to better reflect this, and also modified the way we refer to this analysis in the conclusion section (P21 L25-28). In addition, we have removed the (no) reservoir groups from Figure 7 in the revised manuscript (Cohen's d effect size) due to the similarity with the LSM/GHM groups. We use the (no) reservoir group as another example of a factor that was found to be important in previous studies, but which we cannot isolate in our study (P18 L3-7).

3. Better justification of the choice of accumulation periods, which are very arbitrary: how different would be the results if different / additional accumulation periods were used? Ideally, a sensitivity analysis should be conducted. Are the statistical metrics used appropriate? (Point also raised by Referee #1) Whilst I understand the rationale, I struggle very much with the analysis of the 'difference in ranks' as they are really arbitrary. For example I very much like fig 3 but find fig 4 might be greatly dependent on the arbitrary accumulation periods.

We apologize that we did not make our choice of SPI accumulation periods clearer. The accumulation periods were based on those commonly used, where possible adding intermediate values to allow more subtle differences to be observed. These accumulation periods are furthermore nearly equidistant in log space.

Additional analyses were performed to determine whether using fewer SPI accumulation periods (1, 3, 6, 12 and 24 months) would impact the main conclusions of this study. As shown in Figure R6, the global patterns of SPI-n are not greatly impacted by this choice. In addition, the global patterns of the difference in rank SPI-n (Figure 4 of the manuscript) are very similar when fewer accumulation periods are used (Figure R7). The values and range of the difference in rank SPI-n change due to the smaller number of accumulation periods, but overall the direction and relative magnitude are similar. In this way, reducing the number of accumulation periods does not have a large effect on the conclusions of this study. We have added a summary of the results of the sensitivity analysis to the revised manuscript (P14 L2-5).

Finally, we address the point related to the statistical tests. As the referee indicated, there are statistical tests that have been designed for ordinal variables, such as Chi-squared and Cramer's V (an effect size metric). However, these metrics treat ordinal variables as categorical variables, which means that the relationships between SPI-n are ignored. In the preparation of this study, we did calculate Chi-squared and found highly significant results ($p < 0.001$) for all tests analyzing SPI-n for different drought types by climate type or season. In the end we chose ANOVA tests because ignoring the relationship between SPI-n seemed unrealistic. This explanation has been added to the methods section (P5 L17-21). In addition, we report outcomes of Chi-squared tests (P12 L1 + 7). See also our response to referee 1's first comment.

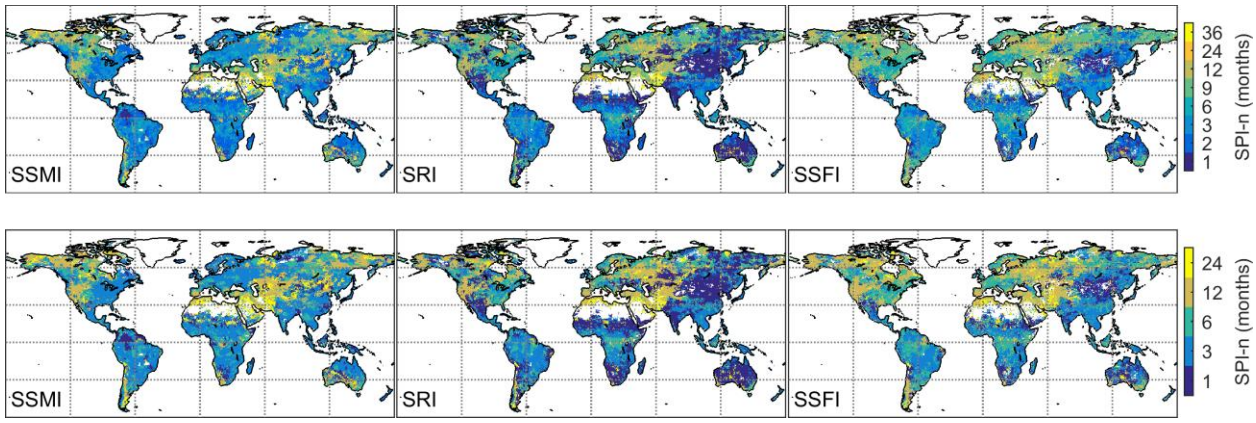

Figure R6. The SPI accumulation period (SPI-n) resulting in the highest correlations with model ensemble mean SSMI, SRI, and SSFI, for summer droughts using the original larger selection of accumulation periods (top) and a smaller selection of accumulation periods (bottom). Pixels where those correlations are not statistically significant ($p < 0.05$) are masked.

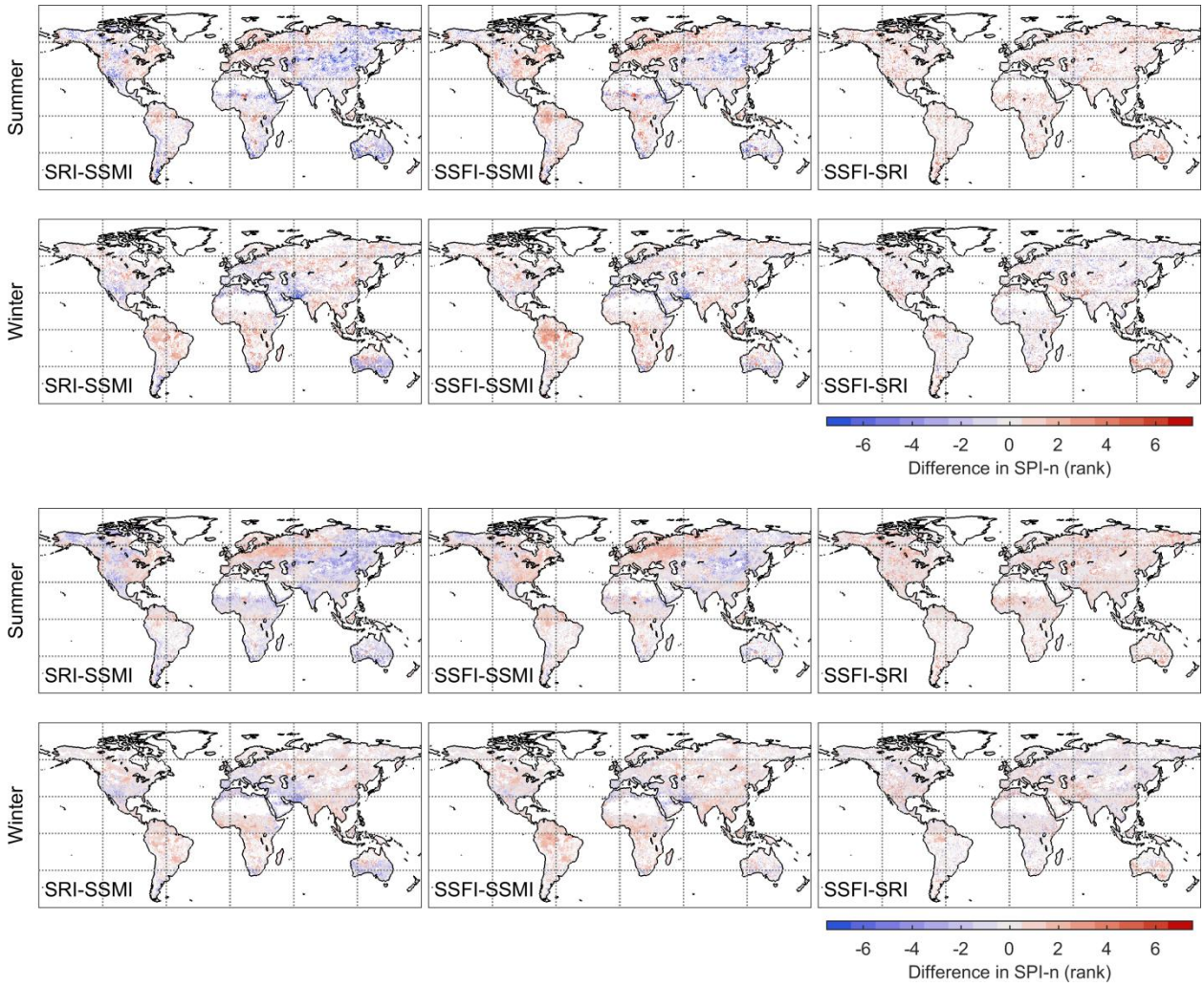

Figure R7. The difference in the rank of SPI-n for SRI and SSMI, SSFI and SSMI, SSFI and SRI for the original SPI accumulation periods studied (top, same as Fig. 4 of the manuscript) and for a smaller selection of accumulation periods (bottom). Pixels where the difference between accumulation periods are not statistically significant ($p < 0.05$) are masked.

4. I find difficult to understand the rationale and use of the evaluation section, as there are no real links with the rest of the analysis/ discussion/ interpretation. I think it is great to have it, but it should be more prominent. Moreover, as the authors mention, the analysis is extremely skewed with a very unequal distribution of catchments geographically. A filtering, with much fewer catchments in US and western Europe should be done. The drainage area of the model extracted points should also be compared with the catchment one. How do the stations relate to the climate zones?

This section evaluates whether drought propagation from meteorological to streamflow drought in the models is similar to observations. Therefore, this is a first reality check for the results shown in the previous sections. We have added the rationale for the evaluation section (P3 L7-8) and added a link to the results in Sections 4.1 and 4.2 (P18 L16-17). The number of GRDC sites does vary considerably over the study sites. While this is unfortunate, removing stations to ensure there are

an equal number of stations per climate type would result in not using more than half of the observational data available.

We did not compare the model and GRDC upstream catchment areas in the first version of the manuscript. In the current version, we applied an additional criteria specifying that the model upstream catchment area may not deviate more than 25% from the size of the GRDC catchment area. This has resulted in significantly fewer stations (126 instead of 297). Not surprisingly, the mean absolute error and Spearman correlations between modeled and GRDC rank SPI-n tend to improve (see revised version of Figure 8). The additional criteria based on the GRDC catchment area has been added to the methods section (P8 L10-11) and the results in section 4.3 have been updated to reflect the new selection of GRDC stations.

5. The method section needs to be re-written, especially the section on timescale propagation, and the rationale and description of the difference analysis p5 l9 to 20; what does mean 'statistical significance test does not reflect the relevance of differences between groups'? What is the group mean (mean correlation? something else?) in equation 1 and 2?

We try to distinguish between "statistical significance" and "relevance" of the difference between groups. That is to say that with a large number of observations as we have in this study, even very small differences between group means can be statistically significant. This sentence has been rephrased in the revised manuscript (P5 L25-27).

The group mean in equation 1 and 2 is the mean rank SPI-n for a specific climate type. This is now specified in the revised manuscript (P6 L1).

The section on evaluation of drought propagation also needs clarifying. Are the RMSE done on daily or monthly streamflow? How well the drainage area of the pixel matches that of real catchment? What model results have to be recalculated and why?

We agree that this section could use some clarification. The RMSE based on monthly streamflow data is used to assign a GRDC station to a model pixel. The streamflow data have been evaluated in previous work (Beck et al., 2017; Schellekens et al., 2016), therefore our evaluation focuses only on the drought propagation, or SPI-n. As stated in response to the previous comment, we have added an additional criteria for GRDC site selection to ensure that the model catchment area is within 25% of the GRDC catchment area. This information has been added to the Methods and Data sections.

The model SPI-n have to be recalculated in the evaluation section because there can be missing values in the observational time series. To ensure we compare like with like, we recalculate the model SI time series, and resulting SPI-n, using only months in which observational data are available. We have rephrased the sentence to make this clearer (P6 L19-21).

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The effect of climate type on timescales of drought propagation in an ensemble of global hydrological models

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Abstract. Drought is a natural hazard that occurs at many temporal and spatial scales and has severe environmental and socio-economic impacts across the globe. The impacts of drought change as drought evolves from precipitation deficits to deficits in soil moisture or streamflow. Here, we quantified the time taken for drought to propagate from meteorological drought to soil moisture drought, and from meteorological drought to hydrological drought. We did this by cross-correlating the Standardized Precipitation Index (SPI) against standardized indices of soil moisture, runoff, and streamflow from an ensemble of global hydrological models forced by a consistent meteorological dataset. Drought propagation is strongly related to climate types, occurring at sub-seasonal timescales in tropical climates and at up to multi-annual timescales in continental and arid climates. Winter droughts are usually related to longer SPI accumulation periods than summer droughts, especially in continental and tropical savanna climates. The difference between the seasons is likely due to winter snow cover in the former and distinct wet and dry seasons in the latter. Model structure appears to play an important role in model variability, as drought propagation to soil moisture drought is slower in land surface models than in global hydrological models, but propagation to hydrological drought is faster in land surface models than in global hydrological models. The propagation time from SPI to hydrological drought in the models was evaluated against observed data at ~~297~~127 in-situ streamflow stations. On average, errors between observed and modeled drought propagation timescales are small and the model ensemble mean is preferred over the use of a single model. Nevertheless, there is ample opportunity for improvement as substantial differences in drought propagation are found at ~~20~~10 % of the study sites. A better understanding and representation of drought propagation in models may help improve seasonal drought forecasting as well as constrain drought variability under future climate scenarios.

1 Introduction

Drought is a complex global phenomenon with severe environmental (Bond et al., 2005; Lewis and Sjöstrom, 2010; Reichstein et al., 2013; Turco et al., 2017; Vicente-Serrano et al., 2013) and socio-economic (Horridge et al., 2005; Stanke et al., 2013; Wegren, 2011) impacts. Data from global and regional models are commonly used to study droughts (e.g.

Andreadis and Lettenmaier, 2006; Sheffield et al., 2004; Sheffield and Wood, 2008a) and water scarcity (Kummu et al., 2016; Veldkamp et al., 2015, 2016, 2017; Wada et al., 2011), and how these will change in the future (Dai, 2013; Huang et al., 2017; Sheffield and Wood, 2008b; Trenberth et al., 2014). However, the evolution of drought from meteorological anomalies to deficits in soil moisture and streamflow in these models is still poorly understood (Van Lanen et al., 2013; Van Loon, 2015), despite the fact that drought impacts are more closely related to these latter components of the hydrological cycle (Van Loon, 2015).

Several types of drought can be distinguished (i.e. Van Loon, 2015; Mishra and Singh, 2010). The first stage or type of drought is called meteorological drought, and is caused by precipitation deficits that may or may not be combined with above-normal potential evaporation rates. If the precipitation deficits and/or increased evaporation rates are sustained for a sufficient period, they can result in lower than average soil moisture availability, which may result in a soil moisture drought. In the same way, meteorological drought can propagate into lower streamflow and groundwater levels, which are both forms of hydrological drought. Another type of drought, socio-economic drought, is not based on a hydrological variable alone, but occurs when water availability is lower than water demand. As drought propagates from meteorological drought to soil moisture or hydrological drought, the characteristics of droughts change. As drought moves through components of the hydrological cycle, the onset of droughts tends to be lagged, there tend to be fewer but longer drought events, and the droughts are attenuated (Van Lanen et al., 2013; Van Loon et al., 2012; Peters et al., 2003). The degree to which these drought propagation characteristics are observed depends on climate and catchment properties (Van Lanen et al., 2013; Van Loon and Laaha, 2015).

Several drought propagation studies have been carried out based on observational data at catchment to national scales, mainly focusing on meteorological and streamflow drought (e.g. Barker et al., 2016; Haslinger et al., 2014; Van Loon and Laaha, 2015; Lorenzo-Lacruz et al., 2013). However, the geographical extent covered by these studies is limited, mainly due to the lack of observational data with sufficiently long timescales needed to identify drought in many regions. Therefore, data from regional or global models are generally used to study drought at larger spatial scales. In some cases, studies have used data from a single large-scale model (e.g. Van Lanen et al., 2013; Lehner et al., 2006; Lloyd-Hughes et al., 2013; Sheffield et al., 2004). However, there can be considerable differences between hydrological outputs of different large-scale models (Burke and Brown, 2008; Gudmundsson et al., 2012b, 2012a; Haddeland et al., 2011; Prudhomme et al., 2014; Veldkamp et al., 2018), suggesting that multi-model approaches (e.g. Gudmundsson et al., 2012a; Stahl et al., 2012; Tallaksen and Stahl, 2014; Wang et al., 2009) are more appropriate. This is supported by the fact that studies have found that a model ensemble performs better than individual models (Gudmundsson et al., 2012a; Stahl et al., 2012). However, most regional or global drought studies have focused on drought frequency and severity (van Huijgevoort et al., 2013; Prudhomme et al., 2011, 2014) rather than on drought propagation, and those that have studied drought propagation have been limited to a single model (Van Lanen et al., 2013) or to a small selection of contrasting catchments (Van Loon et al., 2012).

The aim of this study is therefore to investigate drought propagation times in an ensemble of global hydrological models from meteorological drought to soil moisture drought, and from meteorological drought to hydrological drought. We focus on the effect of climate on drought propagation in particular, and distinguish between summer and winter droughts. In Sect. 2, we describe the identification of drought, the method we use to quantify drought propagation timescales, and the validation analysis. The global models and the observational data are presented in Sect. 3. In Sect. 4, we first describe and discuss the timescales of drought propagation and their relationship with climate types in the multi-model ensemble mean. ~~In addition~~Second, we briefly describe the model variability ~~and~~. Third, we perform a validation exercise to gauge whether propagation from meteorological to streamflow drought in the models resembles observational drought propagation times. We wrap up with a brief summary and conclusion in Sect. 5.

2 Methods

The timescales of drought propagation were determined by relating standardized indices of meteorological drought to indices of soil moisture and hydrological drought. These indices were derived from an ensemble of seven global models that were forced with a consistent meteorological dataset in the eartH2Observe project (Schellekens et al., 2016). For more details on the model and forcing datasets, see Sect. 3. First, we calculated standardized indices of precipitation, soil moisture, runoff, and streamflow ~~were calculated~~ as a measure of drought. Second, we determined which timescales of meteorological drought were most strongly correlated to the other drought types. Finally, ~~the model results were~~we evaluated the modeled drought propagation times against drought propagation times derived from observational data.

2.1 Drought indices

Meteorological drought was quantified by the widely used Standardized Precipitation Index (SPI; Mckee et al. 1993). The SPI fits a pre-defined probability distribution to the frequency distribution of precipitation. Generally, the precipitation series have a monthly resolution, in which case the fitting is done for each month separately. Examples of possible distribution functions are the gamma, Pearson Type III, or log-normal (Guttman, 1999; Lloyd-Hughes and Saunders, 2002; Mckee et al., 1993) functions, though a non-parametric approach has also been developed (Hao and AghaKouchak, 2014). In this study, we use the gamma distribution as the pre-defined probability distribution, as this is commonly considered to be the most suitable (Lloyd-Hughes and Saunders, 2002; Mckee et al., 1993; Stagge et al., 2015). Regions in which months with zero precipitation are common are problematic for the SPI (Wu et al., 2007), so the cumulative distribution function is corrected with the probability of zero precipitation (Naresh Kumar et al., 2009). The fitted probability distribution is then transformed to the normal distribution, resulting in negative (positive) values for dry (wet) conditions. Note that the SPI relates the precipitation amount in a certain month to average conditions at that particular location. In drier climates or seasons, water-limited conditions may be the norm, while in wetter climates or seasons, water stress may not be relevant until severe drought thresholds are reached.

Advantages and disadvantages of the SPI are described in Hayes et al. (1999). A first advantage is that the SPI is relatively simple, requiring only precipitation data as an input. Secondly, the index is flexible. It can be used to compare different timescales of drought by aggregating the input precipitation time series over a number of months, known as the accumulation period (typically 1, 3, 6, 12, or 24 months). Thirdly, the standardization facilitates comparisons of extreme conditions in different locations, but also over different timescales. A disadvantage is that the precipitation data used to calculate the SPI may not be representative of surface conditions. In addition, the calculation of the index requires long time series (>30 years) of data (Guttman, 1999; Mckee et al., 1993; Zargar et al., 2011).

The standardization approach of the SPI is not only easily applied to different timescales, but can also be applied to other (hydrological) variables such as soil moisture or streamflow. In this way, we use the same methodology to identify soil moisture and hydrological drought by defining the Standardized Soil Moisture Index (SSMI) (Hao and AghaKouchak, 2013), Standardized Runoff Index (SRI) (Shukla and Wood, 2008), and Standardized Streamflow Index (SSFI).

Soil moisture and runoff are controlled by pixel-scale precipitation and hydrological processes. Streamflow, on the other hand, is affected by upstream pixels. Therefore, we computed a catchment-aggregated SPI to quantify drought propagation from meteorological to streamflow droughts. The input for the aggregated SPI is the total precipitation falling within each pixel and its upstream area, based on a 0.5° routing network (see Sect. 3). We did not include a travel time factor in this calculation, thus assuming that precipitation falling in the upper parts of each catchment will impact streamflow at the outlet within the same month. In the rest of the paper, meteorological drought is based on the pixel-based SPI when referring to soil moisture or runoff drought, and to the catchment-based SPI when referring to streamflow drought.

In this study, we quantified drought propagation from meteorological drought to soil moisture and hydrological droughts. Therefore, we calculated the SPI using accumulation periods of 1, 2, 3, 6, 9, 12, 24 and 36 months. These accumulation periods span sub-seasonal, (multi-)seasonal, and (multi-)annual timescales. For the other standardized indices (SIs), we used the 1-month accumulation period to identify short-term drought conditions.

2.2 Timescales of drought propagation

Drought propagation from meteorological to soil moisture or hydrological drought was based on correlations between the SPI and target SI (SSMI, SRI or SSFI). The SI time series were prepared by applying two criteria to the target SI. First, we distinguished between drought conditions in summer and winter seasons. The summer (winter) season was defined as June, July, and August above (below) the equator, and December, January, and February below (above) the equator. Second, we focused on months corresponding to dry conditions, here defined as $SI \leq 0$. This threshold includes near-normal and mildly dry conditions, but leaves a larger sample size than when we limit the analysis to moderate or severe drought events. Theoretically, moderate drought events ($SI \leq -1$) have an occurrence probability of about 16 % per year, which would correspond to about 5 ~~events~~drought months in a 30-year study period, for a total of 15 ~~events~~drought months considering a three-month season. Severe drought events ($SI \leq -1.5$) would result in six ~~events~~drought months during a 30-year period of three months based on the same reasoning, compared to 45 events using $SI \leq 0$ as a threshold.

After preparing the SI time series, we cross-correlated each of the SPI time series with the SSMI, SRI, and SSFI, without considering lag between the time series. The drought propagation timescale was defined as the SPI accumulation period that is most closely related to the target drought index, which we call SPI-n. In this analysis we determine which SPI accumulation period best represents drought propagation timescales overall during the study period. However, drought propagation may occur at different time scales in the same location and season, and any specific meteorological drought event may propagate to other droughts more quickly, or more slowly, than suggested by SPI-n. Pixels where the final correlations between SPI-n and SSMI, SRI, or SSFI are not statistically significant ($p = 0.05$) were masked from the results. Autocorrelation is a potential issue when correlating time series, as it reduces the degrees of freedom compared to a standard significance test. In this study, the effective degrees of freedom are based on the modified Chelton method (Pyper and Peterman, 1998) as in Barker et al. (2016).

The strength of the relationships between the Köppen-Geiger climate type classification (Kottek et al., 2006) shown in Fig. 1, as well as certain model characteristics on SPI-n, were quantified using a variety of tests. We used the rank of SPI-n rather than the duration of the accumulation period in months in the calculations. This means we assumed that the difference between accumulation periods of 12 and 24 months (both in the order of annual timescales, differing by one rank SPI-n) to be equivalent to the difference between 1 and 2 months (both in the order of sub-seasonal timescales, differing by one rank SPI-n), but very unlike the difference between 1 and 12 months (sub-seasonal versus annual timescales, differing by 5 rank SPI-n). ~~Statistical significance was based on (paired) t-tests and ANOVA tests. Since statistical significance does not reflect the relevance of differences between groups, we~~ The choice of statistical tests is not straightforward. Rank SPI-n are essentially ordinal variables, which are tested using metrics such as Chi-squared. However, Chi-squared and comparable tests treat ordinal variables as categorical variables. In our case this means that the relationships between the used accumulation periods are not taken into account. Since the chosen accumulation periods are nearly equidistant in log space, we chose to apply statistical tests developed for interval data in addition to Chi-squared. Statistical significance was based on ANOVA tests, with the Tukey's honestly significant difference test as a post-hoc test to compare groups in a pairwise fashion. Tukey's test corrects for family-wise errors, or the fact that the chance of type 1 errors increases when comparing multiple groups. When only two groups are possible we used paired t-tests.

With large quantities of data, even very small differences between group means can be statistically significant. Measures of effect size are more useful to investigate the magnitude of the differences between groups, which may be more relevant for interpretation and policy. We use Cohen's d to quantify the effect size between two groups (Cohen, 1988). This metric is defined as:

$$d = \frac{\mu_1 - \mu_2}{\sigma_{pooled}} \quad (1)$$

where

$$\sigma_{pooled} = \sqrt{\frac{(n_1-1)\sigma_1^2 + (n_2-1)\sigma_2^2}{n_1+n_2-2}} \quad (2)$$

and where μ represents the group mean, here mean rank SPI-n, σ the standard deviation of rank SPI-n, *n* the number of observations, and subscripts indicate the group~~-~~, here climate types. The outcome of the metric is thus the difference in group means relative to the standard deviation of the groups. A result of 1 ~~therefore~~ means that the group means differ by one standard deviation and thus that those groups overlap by about 62~~-~~ %. Previous studies tend to use fixed thresholds to interpret small (0.2), medium (0.5) and large (0.8) effect sizes, though these thresholds are considered to be rather arbitrary (Cohen, 1988; Lenth, 2001).

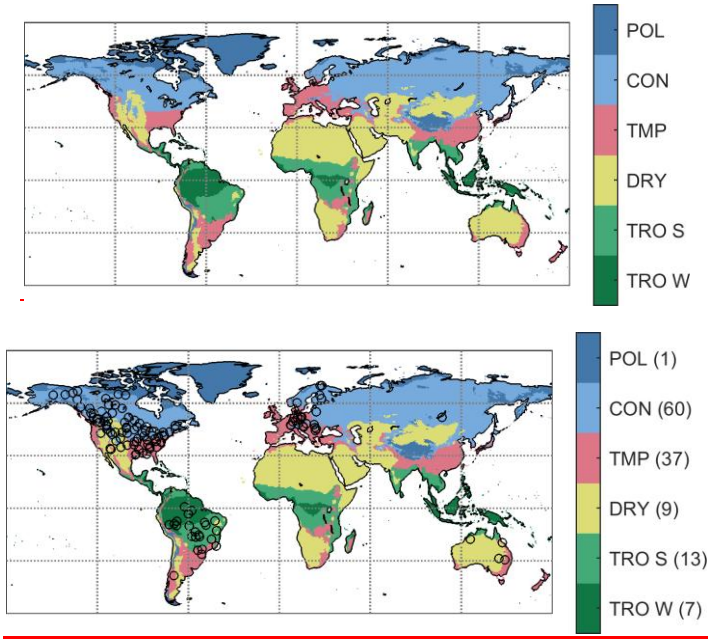


Figure 1: Map of the Köppen-Geiger climate classification and the GRDC stations used in this study. The number of GRDC stations within each climate type is included in the legend in brackets. TRO W = tropical wet, TRO S = tropical savanna, DRY = dry, TMP = temperate, CON = continental, POL = polar.

2.3 Validation of drought propagation

Timescales of drought propagation from meteorological to streamflow drought in global hydrological models are validated against observational data. Sites with observational streamflow data were matched to model pixels by selecting the model pixel containing the in-situ site. Since there may be discrepancies between the model and actual river routing schemes, we extracted the model streamflow data from the selected pixel as well as from the eight surrounding pixels. The in-situ site was then assigned to the model pixel with the lowest root mean square error (RMSE) between observed and modeled monthly streamflow. Once the in-situ sites were matched to model pixels, the SPI-n were calculated as described in Sect. 2.2. ~~For consistency~~Since the observational time series may have gaps within the study period, model results were also recalculated at the in-situ sites using ~~a paired~~only months for which observational data ~~approach~~were available.

Model discharge time series from the models used in this study (see Sect. 3) have been evaluated in previous studies (Beck et al., 2017; Schellekens et al., 2016), so we limit the evaluation to drought propagation characteristics, or SPI-n. The evaluation of SPI-n was based on the rank SPI-n rather than the length of the accumulation period in months, for the same reason for which rank SPI-n were used in the statistical tests (Sect. 2.2). The performance metrics used in the evaluation were mean absolute error (MAE) and Spearman correlation coefficient.

3 Data

We assessed drought propagation in seven global models from the eartH2Observe project (www.earth2observe.eu), as well as in the model ensemble mean. Three of the models are land surface models (LSMs): HTESSEL-CaMa (Balsamo et al., 2009; Yamazaki et al., 2011), ORCHIDEE (D'Orgeval et al., 2008; Krinner et al., 2005; Ngo-Duc et al., 2007), and the SURFEX-TRIP modeling platform (Decharme et al., 2010, 2013). The other four models are Global Hydrological Models (GHMs): LISFLOOD (Van Der Knijff et al., 2010), PCR-GLOBWB (van Beek et al., 2011; Wada et al., 2014), W3RA (van Dijk, 2010; Van Dijk et al., 2014), and WaterGAP3 (Döll et al., 2009; Flörke et al., 2013). Other models in the eartH2Observe project were excluded because they did not provide all of the variables required for this study. The models are run with a consistent 0.5° meteorological forcing dataset, the WATCH Forcing Data methodology applied to ERA-Interim reanalysis (WFDEI) data (Weedon et al., 2014). However, static fields such as land cover and soil physical properties were not prescribed, as these tend to be closely linked to the modeling system. Important characteristics of the models such as runoff mechanisms and representation of reservoirs or water use are presented in Table 1. For more information about the model datasets and project design, see Schellekens et al. (2016). Since we cannot disentangle the effects of the differences in model structures and parameterizations in the current experimental design, we focus on the results of the model ensemble mean rather than the individual models. The ensemble mean provides insight into the model consensus on drought propagation time scales and how these vary by climate. Nevertheless, we present the individual model results in the Supplementary Information.

In this study, we used the monthly precipitation, root-zone soil moisture, runoff, and streamflow datasets to calculate the SIs. We do not study groundwater droughts because HTESSEL-CaMa does not simulate this store, and two of the other models have not made the data available. In addition, groundwater is defined differently between models, complicating comparisons of this store. The common forcing dataset means that the SPI time series are identical for all models, while the SSMI, SRI, and SSFI are model-specific. The model ensemble mean was calculated as the average of the SIs. This method deviates from the standard approach in which the ensemble mean is the average of the original model time series. We have chosen to average SI time series because root-zone soil moisture storage and its variability vary considerably between models in certain regions. In this way, models with high soil moisture (variability) have a much larger influence on the mean time series than models with low soil moisture (variability). In these situations averaging SI time series better captures the overall model response than averaging original model time series (see Fig. S1 for an example). Though averaging SI time series will result in a narrower range of values for the ensemble mean than for the individual models, the outcome of the SPI-n analysis is not greatly affected because it is based on correlations. A consistent model dataset for the eartH2Observe project is available from 1980–2012, though we use the years 1983–2012 to avoid data gaps in the first years of the SI time series caused by the 36-month accumulation period for the SPI. In addition to the datasets used to calculate the SIs, we used other model variables to relate these to the drought propagation results. These are the runoff coefficient, or the ratio of runoff to precipitation, and the ratio of surface runoff to total runoff.

Table 1: Overview of models and relevant characteristics

Model	Model type	Evaporation	Snow	Soil layers	Runoff	Reservoirs	Water use
HTESSEL-CaMa	LSM	Penman-Monteith	Energy balance	4	Saturation excess	No	No
LISFLOOD	GHM	Penman-Monteith	Degree-day	2	Saturation and infiltration excess	Yes	Yes
ORCHIDEE	LSM	Bulk method (Barella-Ortiz et al., 2013)	Energy balance	11	Green-Ampt infiltration	No	Irrigation only
PCR-GLOBWB	GHM	Hamon	Temperature based	2	Saturation excess	Yes (lakes only)	No
SURFEX-TRIP	LSM	Penman-Monteith	Energy and mass balance	14	Saturation and infiltration excess	No	No
W3RA	GHM	Penman-Monteith	Degree-day	3	Saturation and infiltration excess	No	No

WaterGAP3	GHM	Priestley-Taylor	Degree-day	1	Beta function	Yes	Yes

The validation of modeled drought propagation was based on observed precipitation and streamflow time series. We used gauge-based precipitation data from the Global Precipitation Climatology Centre's (GPCC) Full Data Reanalysis product version 7 (Schneider et al., 2015). The data are available as monthly precipitation totals at 0.5° resolution for the entire modeled period. Note that reanalysis precipitation data, such as used for the model forcing in this study, and the GPCC dataset are not truly independent. However, the dependence of reanalysis precipitation on both gauge and satellite observations inhibits the selection of a completely independent dataset with global coverage that also has a record long enough for drought studies. Monthly streamflow data were obtained from the Global Runoff Data Centre (GRDC; Koblenz, Germany; http://grdc.bafg.de) database. We used only sites with a catchment area larger than 9000 km^2 ~~and~~, where the model upstream catchment area is within 25 % of the GRDC upstream catchment area, and which have at least 15 years of data. In addition, we ensured that the sites were independent by searching for the most upstream stations that fit the previous requirements. All stations located downstream of these stations were excluded from the analysis. Finally, we only report on sites where the correlation between SPI-n and the SSFI was statistically significant ($p < 0.05$). These criteria resulted in ~~297~~127 sites~~,~~ (see Fig 1), with an average data availability of ~~27~~29 years.

4 Results and discussion

Here, we characterize and discuss the timescales of drought propagation from meteorological to soil moisture and hydrological drought at global scale. First, we describe drought propagation in the model ensemble mean and its relationship to climate. This gives us an idea of the model consensus. Second, we assess the variability between models and identify factors that may explain these differences. Finally, we compare the results of the model ensemble mean as well as the individual models to observational data.

4.1 Model ensemble mean

Drought propagation based on SPI-n for the model ensemble mean varies considerably in space, and all timescales from 1 to 36 months are represented in the results (Fig. 2). Summer soil moisture droughts (based on SSMI) are best represented by SPI-n of one or two months in wet regions such as the Amazon, but by much longer SPI-n in dry climates and some boreal regions. Results are more mixed when focusing on runoff droughts (based on SRI). Runoff droughts are most linked to precipitation deficits in the same month in dry climates such as the Sahel, southern Africa, and central Australia. Runoff droughts in other dry regions such as the Middle East, northern Africa, and the western USA, however, are related to much longer precipitation deficits up to several years. The patterns of drought propagation timescales from meteorological to streamflow drought are similar to the patterns ~~from meteorological to~~of SPI-n for runoff droughts, though SPI-n tends to be

slightly longer. Longer SPI-n for streamflow compared to runoff can be expected as streamflow is simply routed runoff. In general, SPI-n are also longer, and drought propagation slower, for winter droughts than for summer droughts (Fig. 2). In this study, we focus on SPI-n rather than the strength of the relationship between SPI and other ~~SI~~SIs. However, the correlations behind SPI-n are generally high, with median values ranging from 0.67 to 0.74, depending on climate and season (Fig. ~~S1~~ S2). The strength of the ~~relationship~~correlation is highest in tropical climates (medians around 0.8) and lowest in polar climates (medians around 0.6).

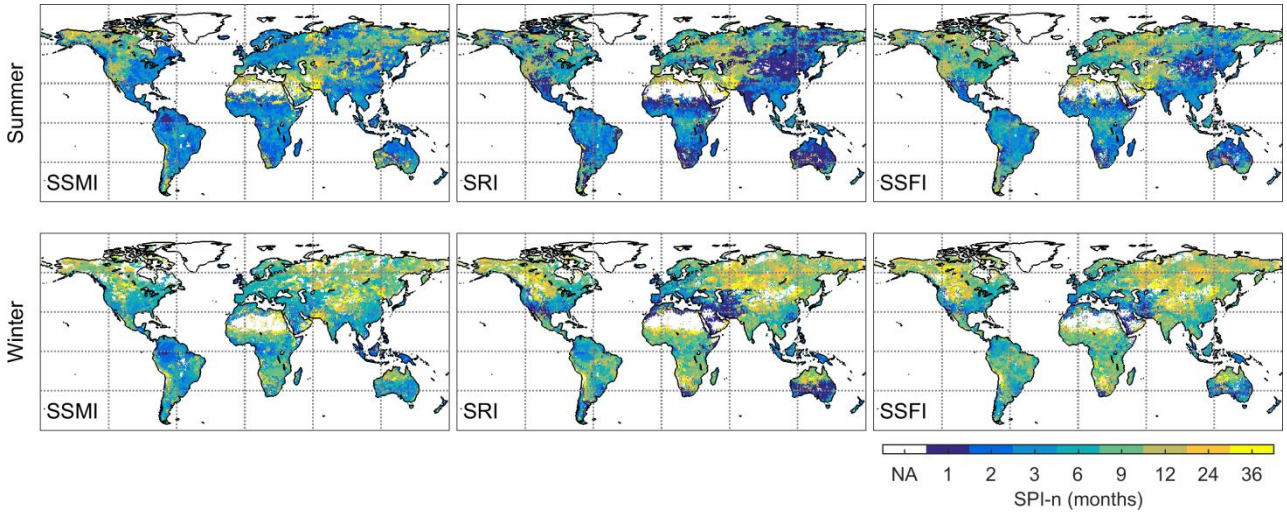
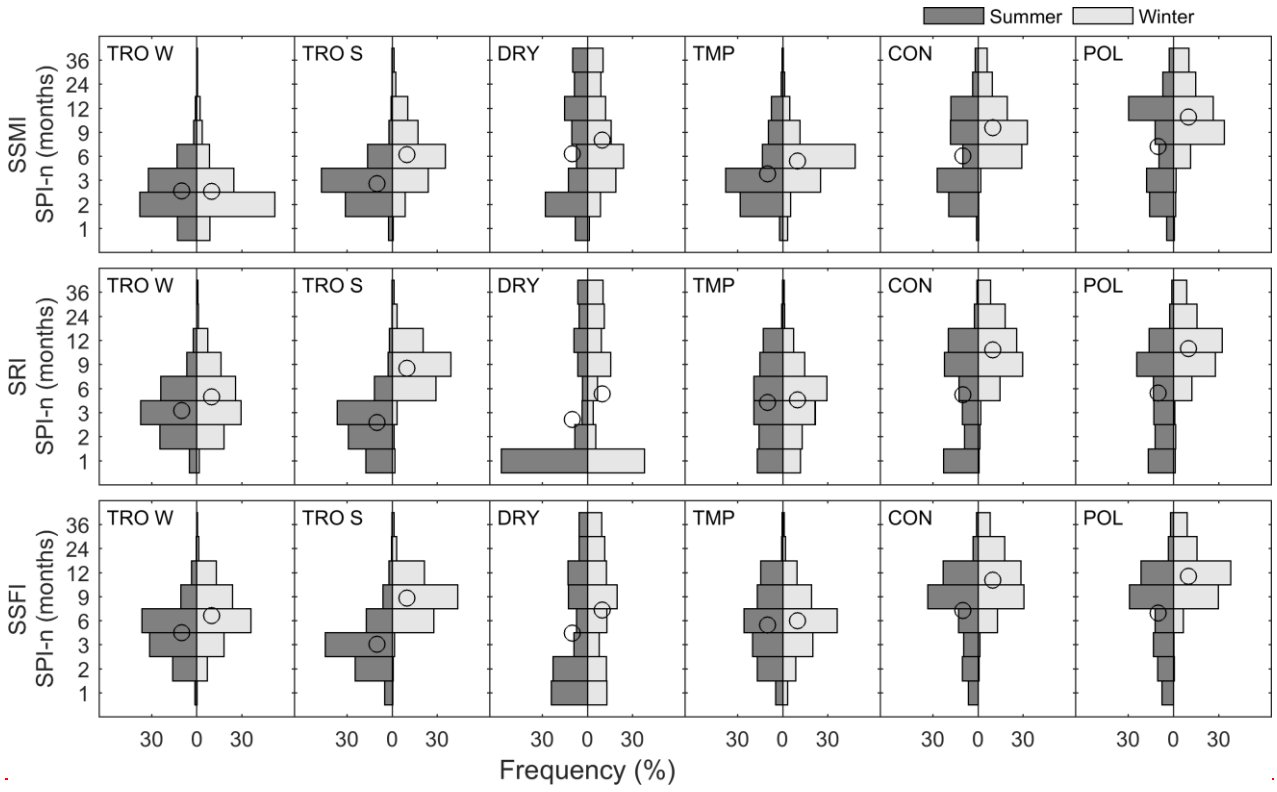


Figure 2: The SPI accumulation period (SPI-n) resulting in the highest correlations with model ensemble mean SSMI, SRI, and SSFI, for summer and winter droughts. Pixels where those correlations are not statistically significant ($p < 0.05$) are masked.

The relationship between drought propagation timescales and climate types is further examined using the Köppen-Geiger classification (Kottek et al., 2006). We use six climate classes that reflect the five major climate types, with an additional distinction between tropical wet (i.e. tropical rainforest or monsoonal climates) and tropical savanna climates (Fig. 1). The results in Fig. 3 confirm that climate type plays an important role in the timescale of drought propagation. As in Fig. 2, droughts in tropical climates tend to respond to short periods of accumulated precipitation deficits, while continental and polar climates respond to longer periods of accumulated precipitation deficits. Overall, the variability within the tropical climate groups (both wet and savanna) is relatively low compared to dry climates, which are represented by the entire range of SPI accumulation periods studied. Despite the large variability in drought propagation timescales in dry climates, further distinctions between desert/savanna or hot/cold climates within the dry climate class did not have added value.


Summer
Winter
SSMI
SRI
SSFI
SPI-n (months)
36
24
12
9
6
3
2
1
TRO W
TRO S
DRY
TMP
CON
POL
30
0
30
Frequency (%)

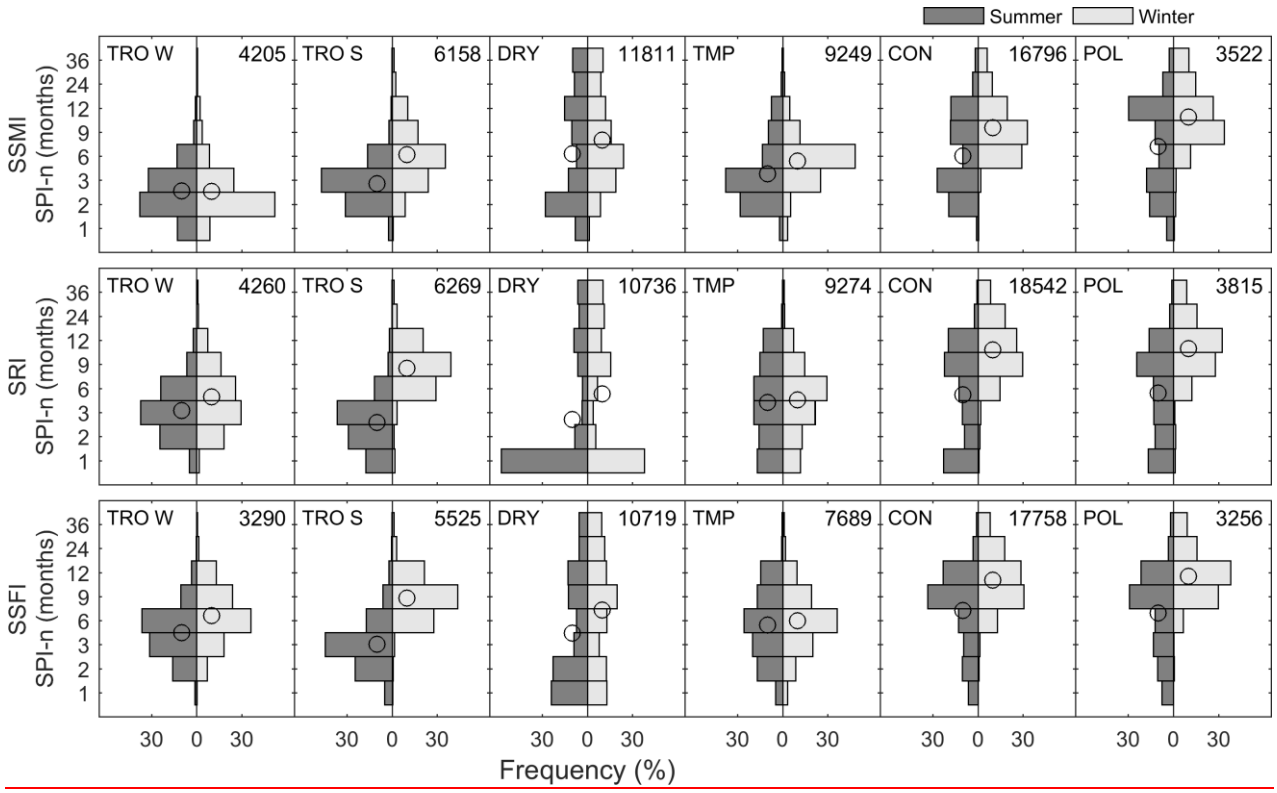


Figure 3: Histograms of the SPI-n in months by climate type, and for summer and winter droughts in SSMI, SRI, and SSFI. Circles represent the mean rank SPI-n per climate type and season and numbers in the upper right indicate the number of summer and winter data pairs per climate and drought type. Abbreviations of climate types are the same as in Fig. 1.

Winter droughts are related to longer SPI-n than summer droughts in tropical savanna, continental and polar climates. Soil moisture droughts in tropical wet climates, and hydrological droughts in temperate climates, on the other hand, have similar propagation characteristics in summer and winter. The seasonality of SPI-n in tropical savanna climates may be related to the distinct wet (summer) and dry (winter) seasons in these regions: SPI-n are more similar to tropical wet climates in summer and to dry climates in winter. In continental climates, longer SPI-n may be due to snow cover in the winter. Precipitation in the form of snow during fall and winter will not replenish soil moisture or runoff until temperatures rise sufficiently to melt the snow. In this way, drought conditions in winter may be more related to precipitation deficits in the previous summer. Indeed, soil moisture droughts may be more related to the SPI accumulated over the three-month period before snowfall than to the longer period starting with those three months and extending until the defined winter season. Note that we used a rather simple definition of summer and winter seasons by using the equator as divider. However, since the climate along the equator is almost exclusively tropical wet, which does not show ~~significant~~large seasonality, we expect that this does not significantly impact the results.

In terms of statistical significance, ANOVA and Chi-squared tests show that the differences in mean rank SPI-n ~~for each~~between climate ~~type~~types are ~~significantly different~~significant ($p < 0.01$) for both soil moisture and hydrological droughts~~,~~. Further analysis based on Tukey's honestly significant difference tests shows that pairwise differences in mean rank SPI-n of almost all climate types are statistically significant ($p < 0.01$) with just one exception. The ~~means of~~mean rank SPI-n for winter hydrological droughts in continental and polar climates are not significantly different. Similarly, the ~~difference~~differences in propagation time between summer and winter droughts for all drought types are significantly different based on Chi-squared and paired t-tests~~,~~ ($p < 0.05$), except for the paired t-test for soil moisture droughts in tropical wet climates. Despite the fact that most group means differ significantly, they are not always substantially different in magnitude. For example, the difference between mean summer and winter SPI-n for runoff droughts in temperate climates is very small.

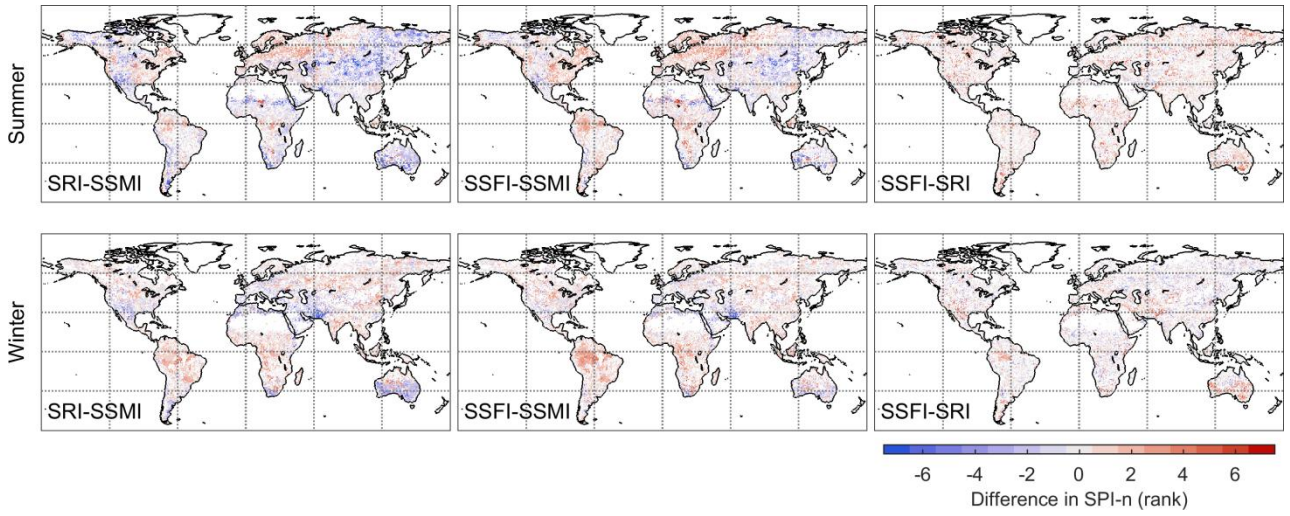


Figure 4: The difference in the rank of SPI-n for SRI and SSMI, SSFI and SSMI, SSFI and SRI. Pixels where the difference between accumulation periods are not statistically significant ($p < 0.05$) are masked.

The difference between the timescales of drought propagation to soil moisture and hydrological droughts can provide additional insights into the mechanisms of drought propagation ~~in the models.~~ The differences in the rank of SPI-n are shown in Fig. 4. As explained in Sect. 2.2, we use rank SPI-n rather than the duration in months because these are more useful in interpreting differences between (sub-)seasonal and annual timescales than the SPI-n in months. A difference of 1–2 rank SPI-n indicates that drought propagation occurs at similar timescales (i.e. sub-seasonal, seasonal or yearly time scales). Differences of more than four rank SPI-n represent large differences in drought propagation timescales, such as between sub-seasonal and yearly timescales. In summer, SPI-n for runoff are higher than for soil moisture in the Amazon, eastern North America, central Africa, and parts of Europe. This means that drought propagation to soil moisture is quicker

than drought propagation to runoff, which suggests that subsurface runoff or baseflow is more important than surface runoff in these locations. The opposite is true for most parts of Australia, large parts of central and eastern Asia, and parts of western North America. In these locations, drought propagation to soil moisture drought is slower than drought propagation to runoff, which implies that surface runoff is an important component of total runoff. The differences can be substantial, with rank differences of five and more, which roughly represent the difference between sub-seasonal and annual timescales. In winter, differences tend to be smaller, and longer drought propagation timescales for runoff than soil moisture (i.e. positive values in Fig. 4) are more common. Drought propagation timescales for streamflow droughts tend to be longer than for runoff drought, which is consistent with streamflow being routed runoff.

Spearman correlation coefficients show that the difference in rank SPI-n of summer soil moisture and runoff droughts is negatively related to the amount of surface runoff relative to total runoff ($\rho = -0.53$). The relationships with average annual precipitation ($\rho = 0.44$) and the runoff coefficient ($\rho = 0.36$) are positive but slightly weaker. Each of the correlation coefficients noted here is highly significant ($p < 0.01$). The amount of surface runoff relative to total runoff, annual average precipitation, and the runoff coefficient are also related to the difference between soil moisture and streamflow drought, though the relationships are slightly weaker (correlations are up to 0.1 lower). The difference in SPI-n between drought types in winter, as well as between runoff and streamflow droughts in summer, cannot be explained by these variables. ~~Each of the correlation coefficients noted here is highly significant ($p < 0.01$).~~

Results of propagation analyses from soil moisture to runoff and streamflow drought, and from runoff to streamflow drought are largely consistent with the results shown in Fig. 4. For example, regions where meteorological drought propagates into soil moisture drought at shorter time scales than it does to runoff or streamflow drought (i.e. red colors in Fig. 4) are represented by longer timescales of SSMI-n (Fig. S3). Regions showing negative values in Fig. 4, on the other hand, tend to be best represented by SSMI-n of one month, or the shortest accumulation period. As discussed previously, hydrological drought may not be preceded by soil moisture drought in these regions: the negative values suggest that surface flow may be more important than subsurface flow, thereby bypassing the soil moisture store. Therefore one-month SSMI-n appear to be the most appropriate, even though the mechanism of drought propagation through surface flow cannot be represented when analyzing the propagation from soil moisture to hydrological drought. Propagation from runoff to streamflow drought largely occurs at short time scales of one to two months, which is consistent with the similarity of the global patterns of SPI-n for these drought types in Figs. 3 and 4.

In an additional analysis, we calculated SPI-n for the model ensemble mean focusing on mild droughts ($SI \leq -0.5$) and moderate droughts ($SI \leq -1$). When using mild droughts as a threshold value, the results are largely similar to those including near-normal conditions ($SI \leq 0$), as shown in Fig. ~~S2~~ S4. Both the global patterns as well as the differences between the climate types are similar to the results shown in this section. However, the number of pixels masked due to insignificant correlations between SPI-n and the SSMI, SRI or SSFI increases. When moderate droughts are used as a threshold (Fig. ~~S3~~ S5), the proportion of pixels that are masked increases further, resulting in 40–50 % less data than when including near-normal conditions. In addition, the maps of SPI-n become noisier and the distributions of SPI-n by climate

type (as shown in Fig. 3) flatten, especially in continental and polar climates. However, the relationships between the climate and seasonal group means remain similar.

Additional sensitivity tests were based on the number of SPI accumulation periods studied and the method used to calculate the ensemble mean. Global patterns of SPI-n (as shown in Figure 2) and the difference in rank SPI-n (as shown in Figure 4) are very similar when fewer SPI accumulation periods are used (1, 3, 6, 12 and 24 months). The outcomes of the Chi-squared and ANOVA tests investigating the differences in SPI-n by climate type are also statistically significant and therefore unchanged. Similarly, calculating the ensemble mean based on the original model time series rather than SI time series has a limited effect on the global patterns of soil moisture and on the average rank SPI-n per climate type. A higher occurrence of longer SPI-n for soil moisture droughts was associated with a substantially higher average soil moisture content and soil moisture variability in one or two models. The model ensemble mean based on averaging soil moisture time series was therefore more sensitive to soil moisture conditions in those one or two models than in the other models (Fig. S1).

The patterns of runoff drought propagation found in this study are similar to a previous study that calculated correlations between ensemble median runoff and precipitation percentiles (van Huijgevoort et al., 2013). Specifically, runoff is more closely related to shorter SPI (or precipitation percentile) accumulation periods in tropical regions, and to longer accumulation periods in continental and polar climates. However, more specific regional comparisons between these studies are hindered by differences in the approach of the two studies. In Van Huijgevoort et al. (2013), correlations are based on the full precipitation and runoff time series, while in our study they are limited to below-average runoff conditions in either summer or winter months only. The results shown here are also in line with results from an observational study comparing SPI and SSFI in the United Kingdom performed by Barker et al. (2016). Barker et al. (2016)~~That study~~ reported that SPI-n of 1–4 months were most closely related to SSFI, except in the southeast where some major aquifers are located and where longer SPI-n were found. That is just slightly shorter than the 2–6 months found in this study. Where drought propagation occurs at very short timescales, drought is mainly driven by precipitation deficits, possibly in combination with temperature anomalies (though these are not reflected in the SPI). Where drought propagation occurs at long timescales, attenuation by hydrological stores likely plays a more important role.

4.2 Model variability

The variability of SPI-n in the models underlying the model ensemble mean is shown in Fig. 5. Again, the standard deviation is not shown in months, but in the rank of SPI-n timescales studied. In summer, the standard deviation ranges from 1–4 rank SPI-n. Note that differences of 1–2 rank SPI-n indicate that models tend to agree on whether drought propagation occurs at sub-seasonal, seasonal, or annual timescales. Model variability is low in temperate regions such as Europe and eastern North America, as well as in tropical regions such as the Amazon and Southeast Asia. The model variability is high in (semi-)arid regions such as the Sahel and central Australia. The patterns of model variability in hydrological drought propagation timescales are largely similar to those of soil moisture drought. However, the variability is patchier, and there are some regional differences. For example, model variability in SPI-n in tropical and temperate climates is slightly higher for runoff

than for soil moisture. In addition, model variability is lower in central Asia for runoff droughts than for soil moisture droughts.

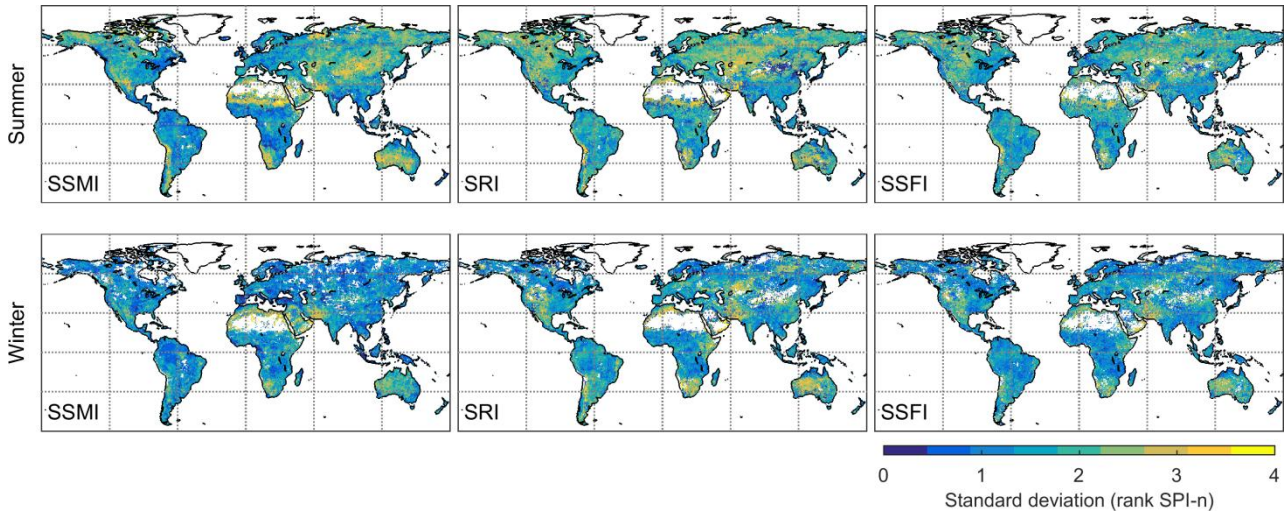


Figure 5: The standard deviation of the rank of SPI-n between the different hydrological models for summer and winter droughts in SSMI, SRI, and SSFI.

Attributing observed differences between models to model characteristics is not straightforward, despite the common meteorological forcing, because there are considerable differences in model structures and parameterizations (Beck et al., 2016, 2017; Döll et al., 2016). However, we examine the relationship between drought propagation and specific model characteristics to identify areas for further study. First, we examine the relationship between SPI-n and average soil moisture storage, as previous work has suggested that water storage plays an important role in drought propagation (Barker et al., 2016; Van Loon and Laaha, 2015). In addition, we examine the effect of model structural choices on drought propagation in an exploratory analysis.

Soil moisture storage in the models varies considerably between models, mainly due to differences in the definitions of root-zone soil moisture used to calculate the SSMI. The reported depths of the root zone range from 0.2 to 8 m, which may be a fixed value for all pixels or vary by pixel and/or land use type. Although we use standardized indices (SSMI) and not absolute values of soil moisture, the response time to changes in precipitation and/or evaporation will differ between soils with large and small storage volumes. We examine the relationship between average root-zone soil moisture storage and average SPI-n for soil moisture droughts per climate type in Fig. 6. Soil moisture storage is averaged over space and time, and SPI-n in space, resulting in a single point for each model. The figure shows that drought propagation from meteorological to soil moisture drought is strongly related to average soil moisture storage, with correlation coefficients between 0.56 and 0.91, depending on the season and climate type. The impact of changes in storage on drought propagation

is especially high in dry climates, where relatively small differences in average soil moisture correspond to large differences in SPI-n. In comparison, the impact of storage on SPI-n is low in tropical wet climates. In general, changes in SPI-n with storage are smaller in winter than in summer. For tropical wet, continental, and polar climates the impact of storage is less than one rank SPI-n over the full range of storage volumes in winter, suggesting that storage is not an important driver of model variability in this season.

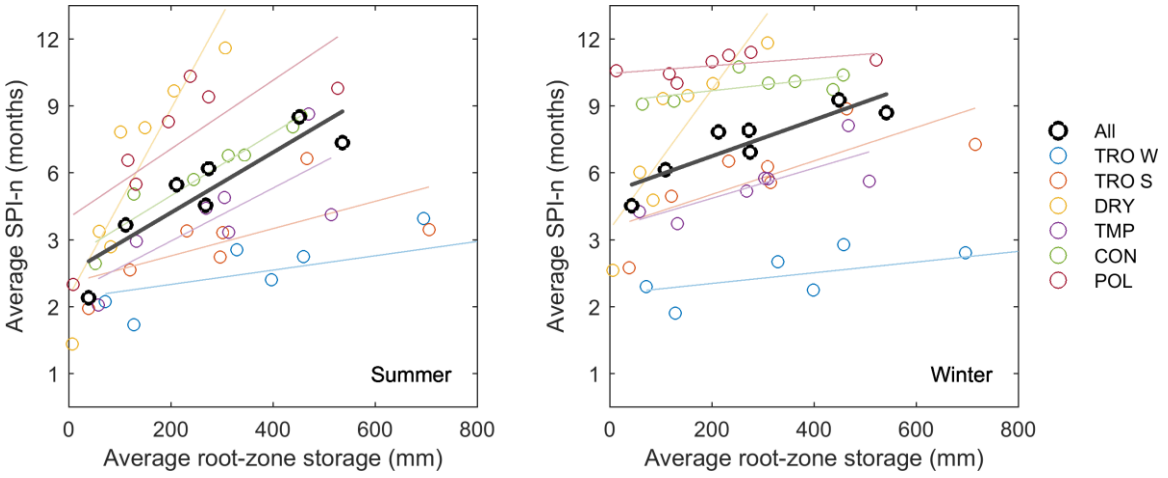


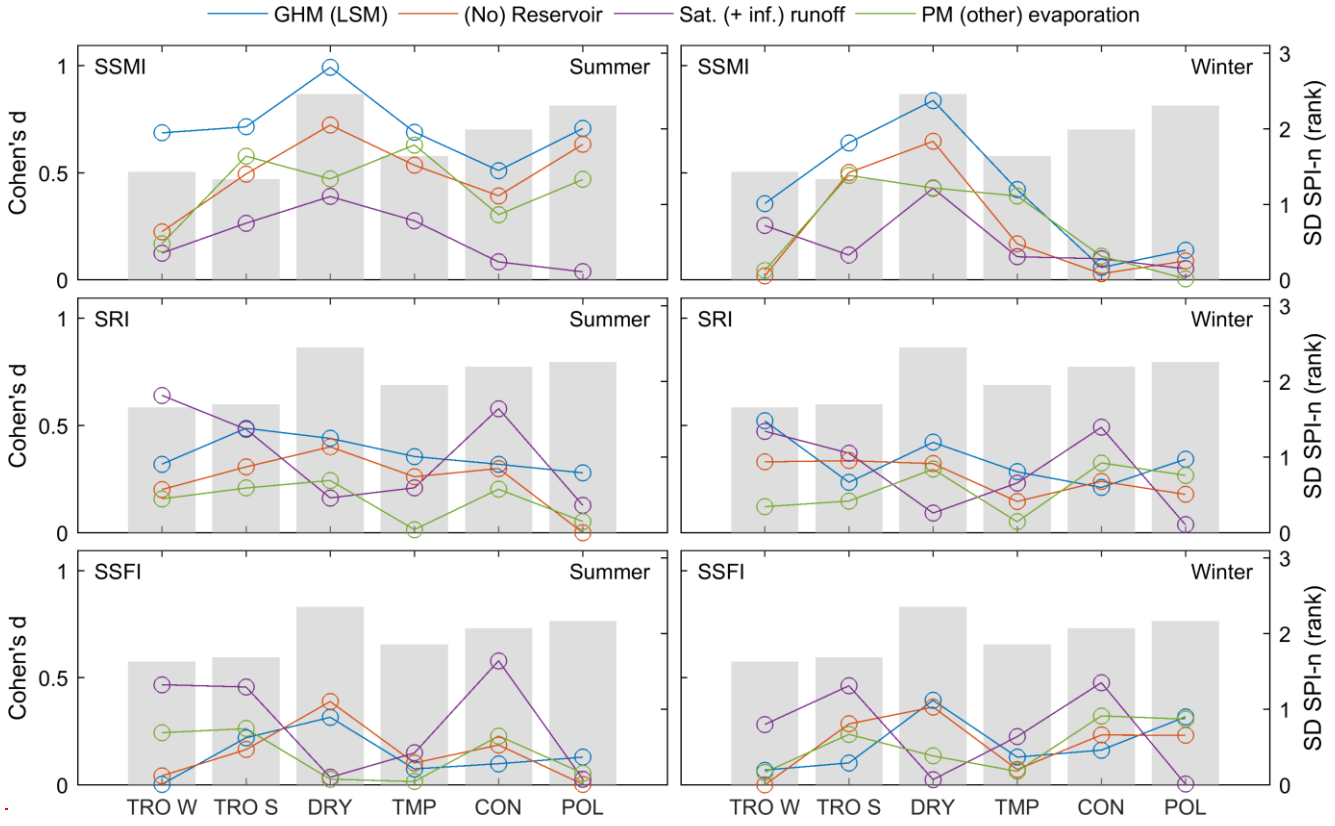
Figure 6: SPI-n for the SSMI averaged over all pixels and each climate type separately plotted against mean annual root-zone soil moisture storage averaged over the same region. Each point represents a model. Lines of best fit have been added for reference.

The relationship between soil moisture storage and drought propagation to runoff and streamflow is not included here because the link is not as clear-cut. Runoff consists of surface and subsurface components. The subsurface component of runoff is related to water stored in groundwater and/or in the lowest layer of the soil, and not to the upper soil layers included in the root zone. Furthermore, groundwater data are not available for three out of seven models. The surface component, on the other hand, is only affected by soil moisture in as much that saturated conditions near the surface will result in a larger surface flow component. Therefore, it is impacted by the relative saturation of the soil rather than the storage itself.

In an exploratory analysis, we also examine the relationship between four qualitative factors related to model structure and the timescales of drought propagation. First, we compare SPI-n in LSMs and GHMs. Second, we study the effect of different evaporation schemes, specifically comparing Penman-Monteith evaporation schemes to more empirical temperature-based approaches. ~~Third, we compare models that represent reservoirs with those that do not. Fourth~~Third, we group models by runoff generation mechanisms, comparing models that include infiltration excess runoff generation to those that only represent saturation excess. In this last analysis, we exclude ORCHIDEE and WaterGAP3 because they use alternative methods of runoff generation; a Green-Ampt infiltration and a beta function, respectively.- Note that the limited number of models and large number of different model parameterizations and structural choices means that we cannot definitively

attribute observed differences between models to any of these characteristics. Instead, this analysis is meant to be an initial exploration of the results.

The relative importance of these model characteristics based on Cohen's d (see Sect. 2.2) varies considerably over the different climates and drought types (Fig. 7). Overall, the tested model characteristics ~~have a~~are associated with larger ~~effect~~effects on soil moisture droughts than on runoff and streamflow droughts. Grouping models by model type has the largest effect on mean soil moisture drought SPI-n for most climates, where drought propagation is slower in LSMs than in GHMs. For runoff droughts, on the other hand, GHMs tend to have higher SPI-n for runoff droughts than LSMs. However, ~~it is unclear whether the representation of the energy balance is~~ we cannot determine which underlying or associated model characteristics are the primary ~~source~~sources of the difference between the groups~~, or whether underlying or related model characteristics are key~~ in this analysis.



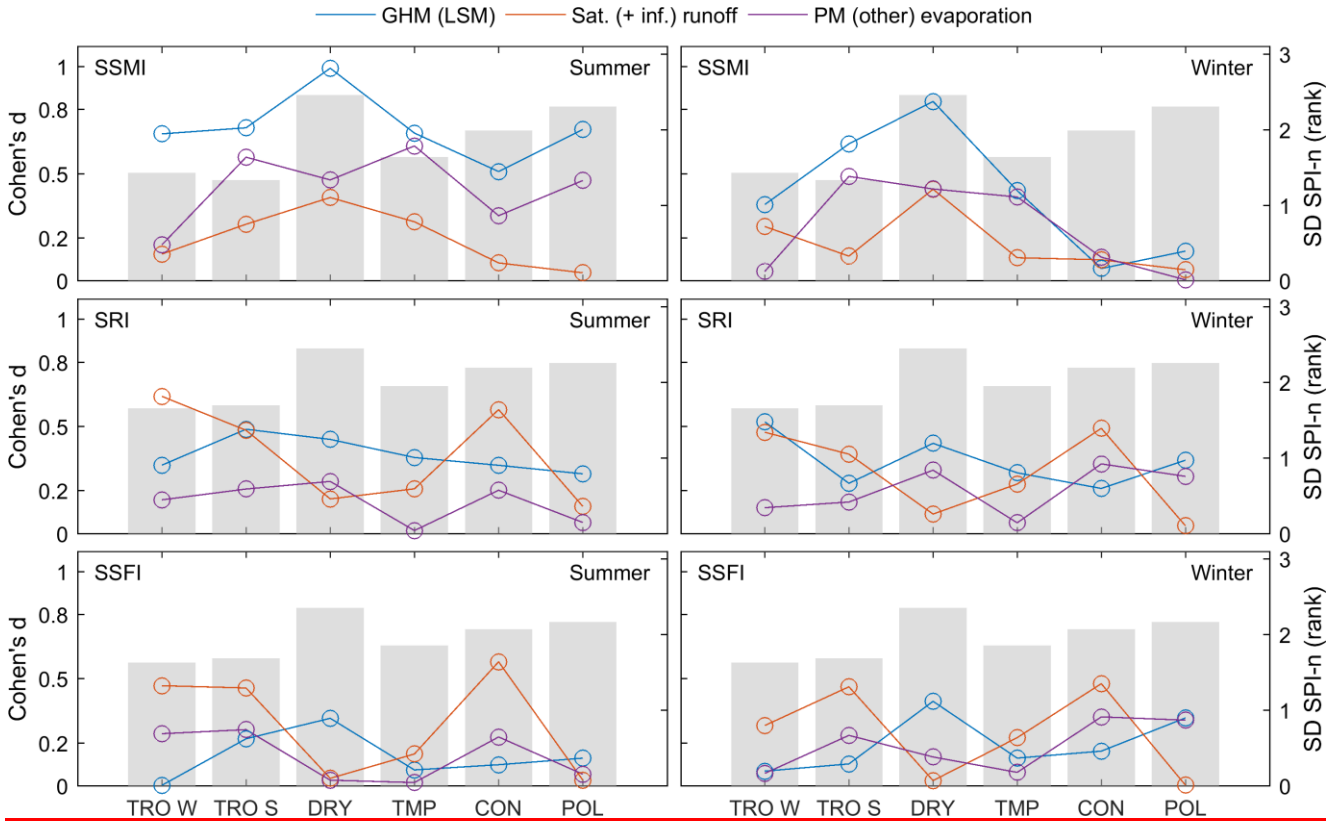


Figure 7: Effect sizes based on Cohen's d for model structural choices by climate for summer and winter droughts in SSMI, SRI, and SSFI. Bars represent the standard deviation of model SPI-n for each group. Abbreviations of climate types are the same as in Fig. 1.

Grouping models by runoff generation mechanisms has a smaller effect on average SPI-n for soil moisture droughts than the other studied factors. However, it can be more relevant for runoff and streamflow droughts, especially in tropical and continental climates. In these climates, including infiltration excess runoff leads to lower SPI-n and faster drought propagation. In tropical climates, this can be explained by the fact that high-intensity rainfall events exceeding the infiltration capacity of the soil are more common.

~~The simulation of reservoirs has a substantial impact on drought propagation, especially for soil moisture and runoff. This is consistent with previous work (Lorenzo Lacruz et al., 2013), and also with increasing recognition that human adaptations should be taken into account in drought studies (Van Loon et al., 2016; Veldkamp et al., 2015). However, it is unclear what mechanism could be responsible for the effect of reservoirs on soil moisture droughts. The way in which reservoirs are implemented in global models affects runoff and streamflow, but has no direct link to soil moisture. Therefore, it is likely that another mechanism is truly responsible for the observed differences.~~

Note that the model characteristics tested here are not fully independent. ~~For example, LSMs are less likely to model reservoirs than GHMs. In addition, t~~ The number of models is small compared to the number of differences in model structures and parameterizations. Therefore, grouping models by different characteristics can result in identical groups, making it impossible to untangle the two in the current study setup. One example is the snow scheme. Previous studies have suggested that using energy-based or temperature-based snow schemes results in different model behavior, both based on the same models used in this study (Beck et al., 2017) as well as in other models (Haddeland et al., 2011). In this study, however, it is impossible to distinguish between model type and snow scheme since all LSMs use an energy-based approach, while GHMs use temperature-based approaches. Another example is simulation of reservoirs. Previous studies have recognized that human adaptation should be taken into account in drought studies (Van Loon et al., 2016; Veldkamp et al., 2015) and that the simulation of reservoirs has a substantial impact on drought propagation (Lorenzo-Lacruz et al., 2013). However, grouping models by whether they simulate reservoirs results in nearly identical groups as dividing them by model type. In fact, only W3RA is classified as another group.

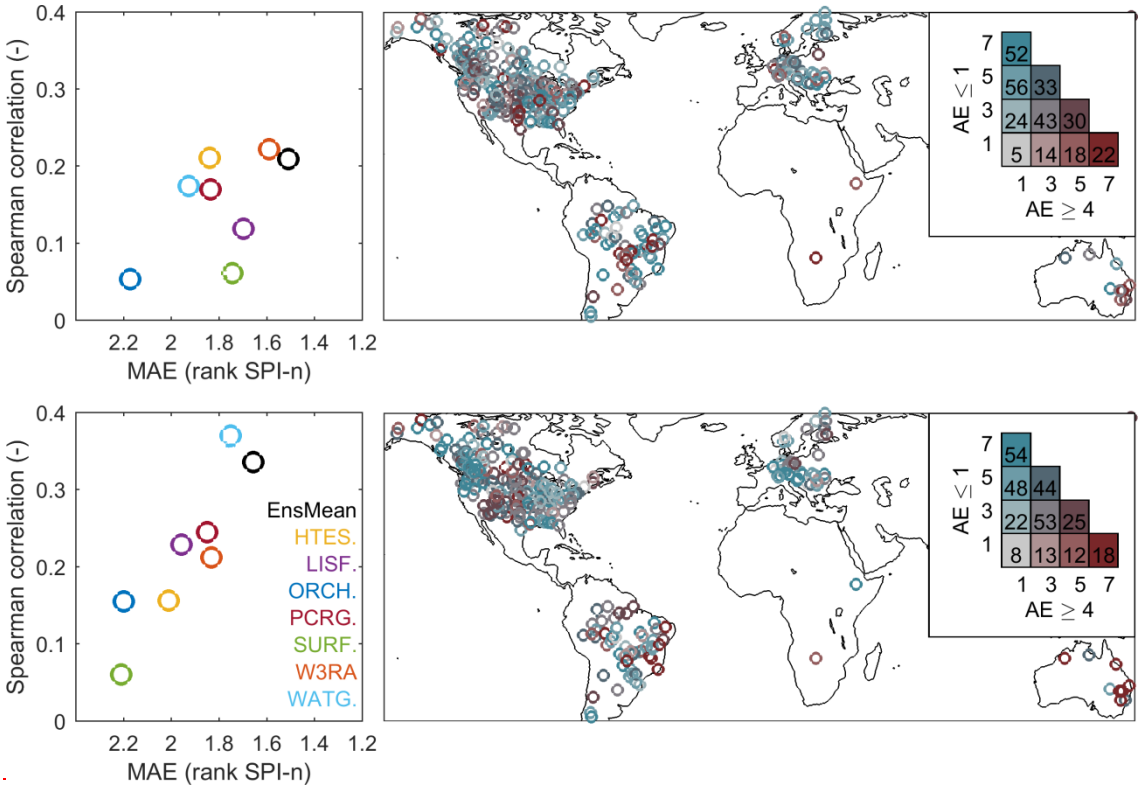
Insight into which factors are truly responsible for model differences can only be gained through exhaustive experiments testing different model parameterizations and structures (i.e. Medlyn et al., 2015). This type of analysis was unfortunately not possible within the experimental setup of this study because model parameterizations were not consistent between models (see Sect. 3). Nevertheless, while the effect sizes cannot be used to confirm that a certain model characteristic is the true factor underlying observed differences, they can be used to identify directions for further study in more comprehensive analyses.

4.3 Evaluation against observations

The timescales of drought propagation from meteorological to streamflow drought in the models and model ensemble mean have been evaluated against data from ~~297~~127 in-situ streamflow stations (Fig. 8). In this way, we can investigate whether the modeled drought propagation times presented in Sect. 4.1 and 4.2 resemble reality. Of the individual models, W3RA performs best for summer droughts and WaterGAP3 for winter droughts based on MAE and Spearman correlations~~.~~ between modeled and observed SPI-n. The performance of the model ensemble mean is similar to that of the best-performing model in both seasons, with the highest correlations and (nearly) the lowest mean absolute errors ~~and the second highest correlations~~ with observed SPI-n. WaterGAP3 is the only model that was calibrated against streamflow observations, which could be a reason for the good performance in winter, even though it is outperformed by all other models in summer. While the mean absolute errors of the ensemble mean and individual models are within one or two rank SPI-n, correlations are low for all models.

In addition to the overall performance metrics, we compare the number of models for which the difference with observed SPI-n is small (absolute error ~~≤~~ ≤ 1) and the number of models for which this difference is large (absolute error ≥ 4) at each site (Fig. 8). The thresholds are based on the models' (in)ability to capture the overall timescales of drought in terms of sub-seasonal, seasonal or yearly timescales. At least six out of seven models are within one step of the observed SPI-n at ~~18~~ 16

and 19 % of the study sites in summer and winter, respectively, and at least four models are within one step at ~~nearly half~~ 45 and 39 % of the study sites ~~(47 and 49 %~~ for summer and winter, respectively~~).~~. This suggests that models are well able to capture observed drought propagation timescales at these sites. However, the majority of models differ by at least 4 steps of SPI-n at approximately ~~20~~ 10 % of sites. At these sites, the models show substantially different drought propagation timescales. These differences in SPI-n correspond to differences between sub-seasonal and annual timescales of drought propagation. Models tend to do well in ~~eastern North America and Europe, as well as~~ western North America ~~in winter~~and Europe, but poorly in central North America and parts of South America and Australia. ~~However, the errors between models and observations are not related to climate, catchment size, or SPI-n.~~



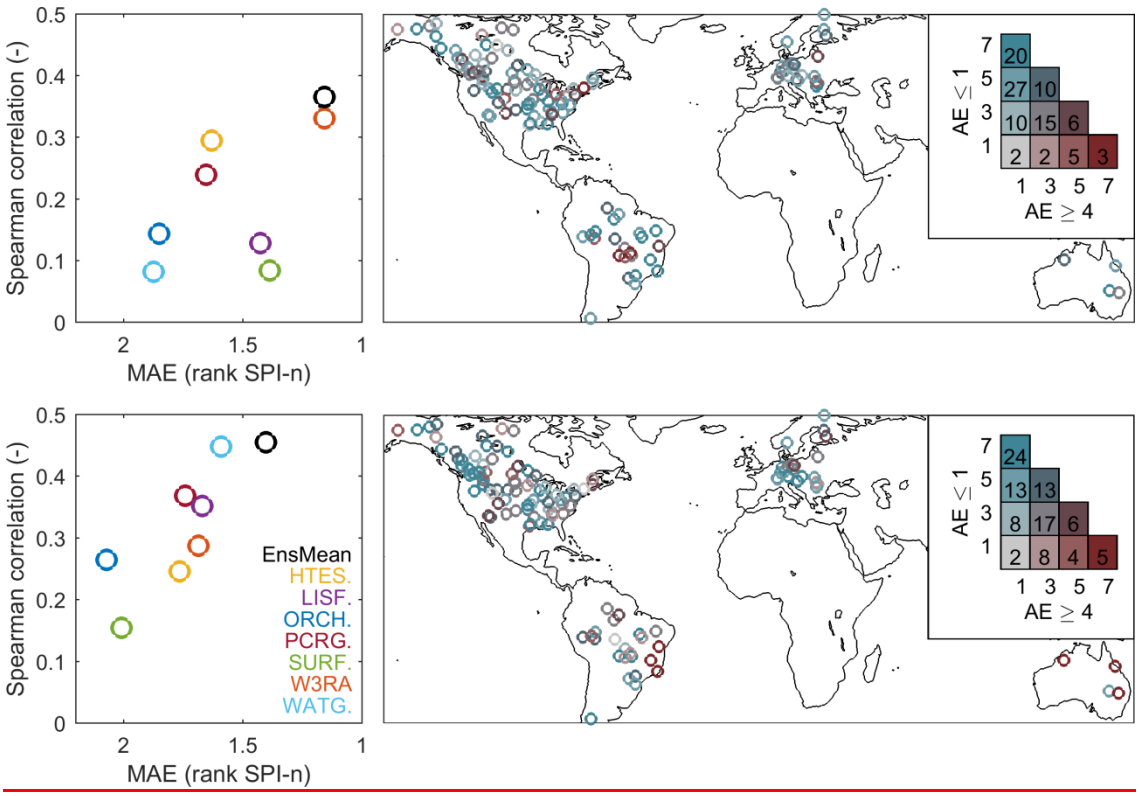


Figure 8: Comparison of model and observed summer (top) and winter (bottom) streamflow drought propagation timescales. The Spearman correlation and mean absolute error based on rank are compared, where better performing models fall in the upper right corner. A map shows the number of models where the absolute error is ≤ 1 or ≥ 4 (right). The number of represented sites is indicated in the symbols of the legend.

We use the mean error (ME) rather than the MAE to investigate the relationship between errors in rank SPI-n and climate type (Fig. 9). While MAE is a more suitable metric for evaluating the overall performance of the models since it is indifferent to the direction of the errors, ME allows us to assess whether models are more likely to over- or underestimate SPI-n and is thus reflects model bias. On average, most models and the model ensemble mean tend to overestimate summertime SPI-n in tropical wet climates, which is also the climate for which mean errors are largest. Models tend to underestimate SPI-n in tropical savanna climates, while results are more mixed in the other climate types (Fig. 9). The confidence intervals of the mean are smallest in continental and temperate climates, which is most likely because a relatively large number of sites are located in these climates compared to the tropical and dry climate types. However, the observed differences in mean rank SPI-n error between climate types are not always statistically significant based on Chi-squared and ANOVA tests ($p < 0.05$). Mean errors in summertime rank SPI-n are significantly different between climate types in only one model (PCR-GLOBWB) according to Chi-squared tests, and in two (HTESSEL-CaMa and PCR-GLOBWB) out of seven models, as well as the model ensemble mean, according to ANOVA tests. In winter, Chi-squared tests show that the differences in mean error rank SPI-n are statistically significant for all but one model (LISFLOOD) as well as the ensemble

mean. The results of ANOVA tests are significant for four models (HTESSEL-CaMa, ORCHIDEE, SURFEX-TRIP and WaterGAP3), but not for the model ensemble mean. Further analysis based on Spearman correlations showed no relationship between errors in rank SPI-n and catchment size.

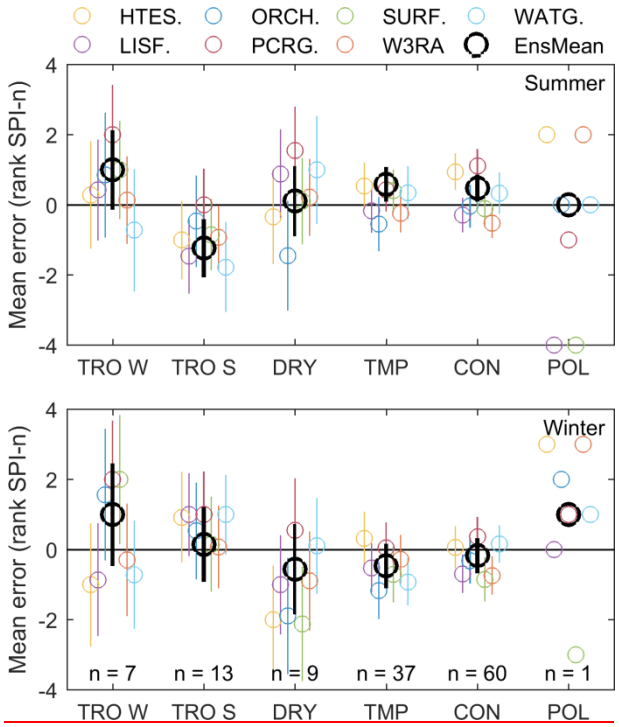


Figure 9: Mean error in rank SPI-n between model and observed summer (top) and winter (bottom) streamflow droughts. Error bars indicate the 95 % confidence intervals of the mean, and the number of sites within each climate type group is indicated in the bottom panel. Abbreviations of climate types are the same as in Fig. 1.

It is important to note that some of the streamflow time series span as little as ~~15~~18 years, which is shorter than the 30 years of data recommended for the calculation of SI. This means that the observational time series at some sites are too short to capture the climatology of their locations. However, the average time series length (~~27~~ 29 years) is close to the required 30 years. Furthermore, even where time series are relatively short we can evaluate whether the models capture the relationship between observed SPI and SSFI during the available time period. Another limitation of the evaluation is that the sites with observed data are not spread evenly across the globe, as most sites are located in the United States or Europe, with scarce data in Africa and Asia. Differences between the models and observations can be attributed to several types of errors (Van Loon, 2015). The first type of error concerns errors in the model meteorological forcing data, but also in the GPCC precipitation data used to create the validation dataset. Then there are the errors in model structure and parameterizations of hydrologic processes, including the representation of anthropogenic influence on streamflow. Finally, there are errors in the (discretization of) the routing schemes employed by the models.

Unfortunately, evaluation of soil moisture drought propagation timescales is inhibited by the lack of root-zone soil moisture data at global scale. While satellite soil moisture products are available, these are limited to the upper few centimeters of the soil (Owe et al., 2008), which is not representative of root-zone soil moisture. Terrestrial water storage data from the Gravity Recovery and Climate Change mission has also been used to investigate drought propagation (Zhao et al., 2017). However, the root-zone soil moisture signal cannot be untangled from the other terrestrial water stores and therefore cannot be used for validation in this study. Field-measured soil moisture is also available, for example through the International Soil Moisture Network (Dorigo et al., 2011). However, only a handful of sites remain after applying the same site selection procedure as for streamflow drought validation (i.e. sufficiently long time series and a statistically significant relationship between SPI and SSMI).

5 Conclusion

This study evaluates timescales of drought propagation from meteorological to soil moisture and hydrological drought in an ensemble of seven land surface and global hydrological models. Drought propagation was quantified by cross-correlating standardized indices of hydrological variables. Here, we focus on soil moisture, runoff and streamflow droughts in summer and winter. However, the simple and flexible approach used here can be applied to other drought types, such as groundwater droughts, and to other months or seasons.

Drought propagation is closely related to climate type, with slower drought propagation in dry and continental climates and quicker drought propagation in tropical climates. Winter season drought propagation tends to be slower than in the summer, especially in tropical savanna and continental climates. This may be a result of the distinct wet and dry seasons in the former, and snow cover in the latter. Faster propagation of meteorological drought to runoff drought than to soil moisture drought has been linked to a higher proportion of surface runoff, thereby causing a larger portion of total runoff to bypass the soil moisture store.

Model variability can be quite high, especially for summer droughts and in dry climates, where the socio-economic impacts of drought can be severe. Since the models were run with consistent forcing datasets, differences can be attributed to model parameterization and structure. For example, drought propagation from meteorological to soil moisture drought was generally slower in models with higher average soil moisture storage, and vice versa. Although the differences cannot be definitively attributed to specific model characteristics in the current experiment, we identified several directions for further study. ~~In addition, grouping~~Grouping models by model type~~,~~ and runoff generation mechanisms~~, and representation of reservoirs all resulted in~~ is especially promising, as these factors are associated with significantly different average drought propagation timescales. A true physical interpretation of the results would require comprehensive experiments in which model structural choices and parameterizations are consistently changed for all participating models. However, this was not possible in the experimental set-up.

The relationship between meteorological and streamflow drought in the global models was evaluated against observational data. Overall, the models were able to capture the timescales of drought propagation, as errors were relatively low on average. However, considerable model advancements can be made since there were large discrepancies between model and observed drought propagation at ~~20~~ 10 % of the study sites.

A better understanding and representation of drought propagation in global models may improve drought forecasting (Cancelliere et al., 2007), especially when combined with the availability of accurate seasonal forecasts (Luo et al., 2007; Luo and Wood, 2007). Drought forecasting potential is expected to be higher in regions with relatively slow drought propagation, such as the dry and continental climates in this study, as drought forecasting for longer SPI-n tends to be more accurate than for shorter SPI-n (Mishra and Desai, 2005). Additional research using lagged SPI-n could assess the potential for forecasting different types of drought based on meteorological data. Improved representation of drought propagation in models is also crucial to constrain the impact of climate change on drought frequency and severity, and thereby improve the reliability of projected changes.

Data availability

The meteorological forcing, model outputs, and standardized indices from the eartH2Observe project are openly available from the project portal (www.earth2observe.eu). GPCC daily precipitation data can be obtained via https://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html and GRDC monthly streamflow data are available at http://grdc.bafg.de.

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