Authors' response to the reviewers' comments

-

Title: Using an integrated hydrological model to estimate the usefulness of meteorological drought indices in a changing climate

-

Submitted to: HESS. Manuscript number: hess-2015-510

Authors: D. von Gunten, T. Wöhling, C. Haslauer, D. Merchán, J. Causapé, O.A. Cirpka

July 3, 2016

We renew our thanks to the reviewers for their useful comments, which improved the quality and the clarity of the paper. We hope that the revised manuscript is now of adequate quality for publication in HESS. The reviewers' comments are addressed in detail below.

1 Responses to the comments of reviewer 1

The modifications related to the comments of the second reviewer are highlighted in blue in the manuscript.

1. **What I find somewhat contradictory in this respect is the low temporal resolution in the applied correlation and regression analysis (and therefore averaged dynamics). The authors use annual hydrological variables. I think that for drought analysis and better understanding drought propagation in the future a sub-annual resolution (at least seasonal dis-aggregation) would be highly desirable. Put differently, how much can we infer from an annual average relation between meteorological drought and streamflow or groundwater levels in contrast to e.g. seasonal data, especially when thinking about water management and planning issues?**

   We are aware that seasonal and sub-annual scales are essential for drought prediction and water management (e.g., Kumar et al., 2016). However, we have conducted our analysis at the annual time scale in this paper because some of the drought indices such PDSI or RDI cannot be directly applied at the seasonal scale. Moreover, the central theme of this paper is the difference between the correlations coefficients (which are similar in all studied climate scenarios) and the model bias/RMSE (which depend on the climate and irrigation scenarios). To study these differences, annual time scale is adequate in our point of view. Indeed, a re-analysis at the seasonal time scale would not change our main conclusion (the need for a hydrological model) but it would unnecessarily lengthen the paper. Finally, the annual timescale is used in many of the published papers on future climate-change impacts (e.g., Kirono et al., 2011; Park et al., 2015), and we wanted to ensure comparability with previous research efforts on this topic. Hence, we have decided to present our analysis for the annual scale in this study. We have summarized our arguments in P5, line 10-15.

2. **A concern that is somewhat related is that very little information is provided about hydrological processes in the catchment (now and changes in the future) and how they relate to differences in the linkage to drought indicators. Is enhanced ET the only factor? I would appreciate to see time series of modeled precipitation, ET, future discharge, groundwater levels etc. for a more process-based picture of the link between a precipitation decrease/ET increase and hydrological drought. This may also help to understand how generalizable the findings from this unique catchment are.**

   We have added a subsection about the hydrological process in the Lerma catchment, focused on the impact of climate change on the hydrology (Sect. 3.5). The aim is to give to the reader a more general picture of the hydrology of the catchment in the different climate and irrigation scenarios. In addition, we have extended the section on future drought (Sect. 4.3) to analyze possible changes in the response of the catchment to droughts in present and future climate (P15, L19-35; P16, L1-4; and Figure 9). We have also included a short remark on the possible generalization of our result to other catchments in Sect. 5 (P16, L28-31).

3. **Regarding the paper presentation, the paper is well written and clearly structured. However, the manuscript would benefit from shortening the methods section (suggestions see below). Although I appreciate the attempt to be very transparent, currently almost 9 pages present methods, and only 5 results and discussion, which seems a bit imbalanced.**

   We have shortened the method section from 9 pages to 4.5 pages (not accounting for the subsection on the climate scenarios, which was displaced to Sect. 3).

4. **"We conclude that meteorological drought indices are able to identify the timing of hydrological impacts of droughts in present and future climate." I am bit concerned about the general inference on timing between the two variables looking at annual averages. What about e.g."summer flash droughts" and intermittent heavy rainfall (likely leading to enhanced surface runoff and less recharge) versus a continuous seasonal dry period versus wetter period? Wouldn't the annual average response be**

similar, but the dynamics between meteorological and hydrological drought and thus water availability and implications for management be different at shorter time scales?

We have noted in the abstract that we concentrated on the annual time scale (P1, L8) and we have reformulated the highlighted sentence to reflect this fact (P1, L18-19).

5. **Since you provide an overview of the methods in section 2.1 some of the later information is a bit redundant and could be heavily shortened.**

   We have shortened Section 2.5 (Section 2.8 in the initial submission) from 40 lines to 31 lines.

6. **P 5, L 6-13: Is this needed in this detail?**

   As we discuss the issue of hydrological versus meteorological droughts in the introduction (P2, L26-32; P3, L1-3), we have decided to remove this paragraph entirely.

7. **Study area: since you provide a detailed description of the basin a link to changes in catchment processes in the future may be interesting to pick up in the results/ discussion.**

   We have added a figure (Fig. 9) and a paragraph to Section 4.3. In this paragraph, we develop our analysis of the differences in the catchment responses to droughts between present and future climate.

8. **Climate scenarios: Could this be shortened and potentially merged with the results 3.1 section (since this section contains quite a bit of methodology in my view)?**

   We have merged the Sections 2.4, 2.5 and 3.1 into the Section 3 which now covers the irrigation and climate scenarios. We have slightly shortened the sections 2.4 and 3.1. The text in Section 2.4 (Section 3.1 in the revised version) is now six lines shorter than in the original version.

9. **Irrigation scenarios: Where does irrigation water come from? Surface water, groundwater abstractions, reservoirs, are there any water transfers?**

   We have added a note on the provenance of the water in Section 3.3 which describes the irrigation scenarios (P11, L1-5). The irrigation water is imported from a reservoir outside of the catchment.

10. **Drought indicators: This section could be strongly condensed. Do you really need the introductory part (P8, L13-30)? P, L23-30: this could go into the discussion section. SPI/SPEI/PDSI are all frequently used. I therefore suggest making reference to existing papers and keeping these methods brief.**

We have moved the description of the drought indices to the appendix and shortened Section 2.6 from 82 lines in the original paper to 30 lines in the revised paper. We have also moved the paragraph on lines 23-30 to Section 4.3 (P14, L7-14).

11. **Computation of potential evapotranspiration: Could some of the details go into an appendix?**

    We have moved this paragraph to the appendix. Only the principal information on potential evapotranspiration were kept in the main text (P6, L8-10 and P7, L26-28).

12. **Methods of comparing the drought indices to predict hydrological variables: Which**

    model are the future drought indicators based on for predicting the hydrological response (e.g. shown in Figure 7)? I assume it is average of the outputs of the four regional climate models as in Figure 6 bottom panel but this information should be given in this section.

    Yes, it is the average of the four climate models. This information was added to the legend of Figure 7.

13. **I would suggest presenting a relative bias rather than an absolute one. In the results you also set the absolute values into context (e.g. P9, L21:"the largest bias is equivalent to only 3.9% of the present water deficit").**

    We agree that presenting the relative bias makes our results more accessible. We have changed the figure as proposed.

14. **Figure 3: There are seasonal differences, which is why I think information may be lost when only looking at annual averages for the correlation/regression analysis**

    We have noted that our results are only valid at the annual scale on P12, L18-19.

15. **Section 3.2: P14, L13:"details are available in the supplementary material": where do I find this?**

    The supplementary material should be available in the HESS website during the review. I will upload it again at least. Please send me a mail if it is still not online, I can also directly send the supplementary material to you.

16. **Figure 5: Is the irrigation scenario a mean of PIRR and FUTIRR or just PIRR?**

    We have modified the label of Figure 5 to clarify the chosen irrigation scenario.

17. **I don't fully agree that the correlation coefficients are all similar, as you write.**

    This point was not described clearly enough. We meant that the correlation coefficients linked with a particular drought index were similar in the present and future climate, not that the correlation coefficients were similar for all drought indices. We have modified this paragraph to clarify our point on P12, L4-7.

18. **How do you explain EDI <0.5? EDI performs especially poor when considering the ETHZ model - any ideas why?**

    After further investigations, the relatively low correlation of EDI with yearly mean discharge and water deficit is probably related to the different weights accorded to the precipitation of each month.

    We can explain this in more detail by looking at the calculation of EDI. EDI is based on the normalization of effective precipitation EP by:

    $$EP = \sum_{n=1}^{i} \frac{\sum_{d=1}^{n} P_d}{n} \tag{1}$$

    where i is the summation period and P_d is the precipitation of d days before the end of the period i. We choose $i = 365$ days in our application. Based on equation (1), daily precipitation is not weighted equally. Precipitation which is close to the last day are given more weight than the precipitation of the day before. Indeed, P_1 is part of each term of the calculation of EP, while P_i is only part of the last term. Practically, it means that precipitation in December is more important than precipitation in January for the calculation of EDI. However, precipitation in January is roughly of the same importance than precipitation in December for the hydrological variables. Hence, EDI is not well correlated with these variables.

    To illustrate this, we have modified the precipitation data. We artificially set the daily precipitation to zero in December, June, or February. We then looked at the influence of this change on the mean EDI. Average EDI is zero in the not-modified data as EDI is normalized on this dataset. EDI based on the precipitation data without rain in December shows the most important change.

    We have added this information to the supplementary material where the correlation coefficients are analyzed in detail (P6, L29-33).

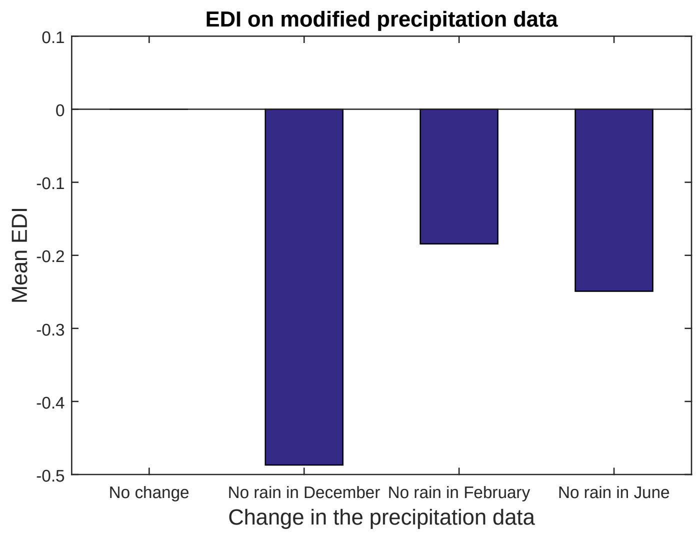

Figure 1: mean EDI for original precipitation data, and precipitation data without rain in December, June, or February.

19. **I think if you decrease the panel size there would be enough space for including the correlation coefficients with water deficit and groundwater head.**

    We did try to plot all the correlation coefficients in the same figure before and it is indeed possible. We have provided this figure with all the correlation coefficients (Q, heads, and water deficit) in the appendix. So the proposed figure is part of the paper and the reader will have access to it. However, we did not include this figure in the main text because the figure is somewhat difficult to grasp in a short amount of time and because it would distract the reader from the major points of our study.

20. **If you start out with three hydrological variables (including hydraulic heads), I would like to see this reflected in this section but currently there is no information about hydraulic heads in the presented material.**

    The correlation coefficients between hydraulic heads and drought indices strongly depend on the position of the wells (see the Figure 1 of the supplementary material). Based on our initial investigations, the model bias is also highly dependent on the well position. The hydraulic heads of one well can react very differently compared to the heads from another well. This makes the interpretation of the various combinations of heads and drought indices complicated. Indeed, there are 12 wells and 7 drought indices. So we need to study 84 different cases to reach some conclusions and these conclusions would only be valid for these particular wells. Hence, the analysis might not be really useful for the reader. Consequently, we have decided to not analyze hydraulic heads further.

21. **Figure 6, right panel: you write that"the relationship between SPEI and discharge is relatively stable in different climates". I find it hard to distinguish the pink from the red dots but to me the slope of the pink or red dot relation looks higher than for the present regression line? Have you considered comparing/plotting regression coefficients for the different indicators and scenarios to go beyond this one SPEI example scatter plot?**

    We have added regression coefficients for the SPEI case in the main paper to provide a more quantitative way of comparing the two figures. We have also modified the colors of this figure. In addition, we provide below two figures which show the regression coefficients for all the drought indices for discharge and water deficit.

22. **Figure 7: Since you have different units for your hydrological variables and to better relate it to the present scenario I would prefer relative over absolute values for model bias.**

    We now use the relative model bias instead of the absolute bias in our analysis.

23. **What about displaying model bias for groundwater head in Figure 7 in addition? What can you infer from the analysis of this variable?**

    For the hydraulic heads, the main conclusion is that the response largely depends on the well localization (see issue #20). Therefore, we should show the model bias for the 12 wells to provide accurate information. It would be a lot of information for one figure. Hence, we prefer to restrict our analysis to discharge and water deficit.

24. **Section 3.4: I am curious about the underlying drivers of the differences between models regarding drought intensity. It seems worthwhile to add some explanations into the discussion section.**

    We have added some comments on this question in Section 4.3 (P14, L32-34 and P15, L1-2).

25. **General: To condense the results section you could omit a few sentences repeating/ explaining methods or introducing figures since the figures are well readable (examples are: P14, L28-31; P15, L11-13).**

    We have shortened the second paragraph on P13, L5-6. (P15, L11-13 in the initial submission).

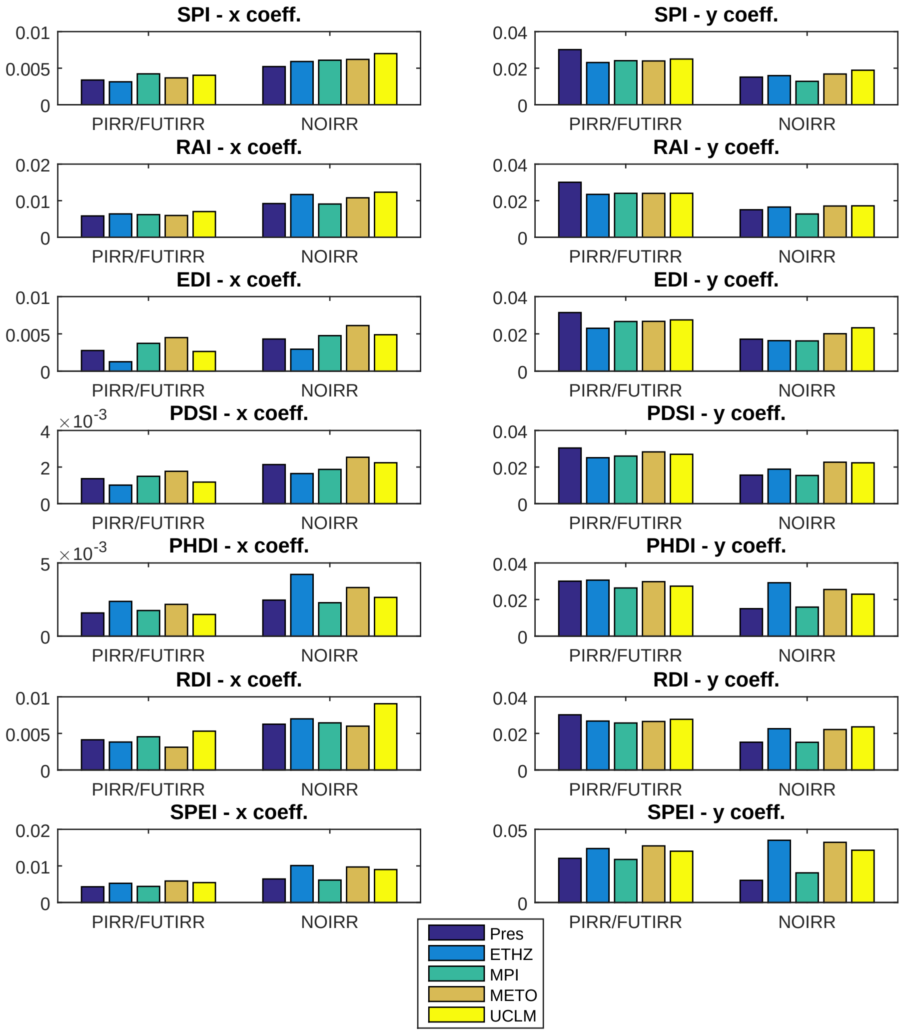

Figure 2: Coefficients of the linear regression of discharge and drought indices for the present climate and the four climate scenarios.

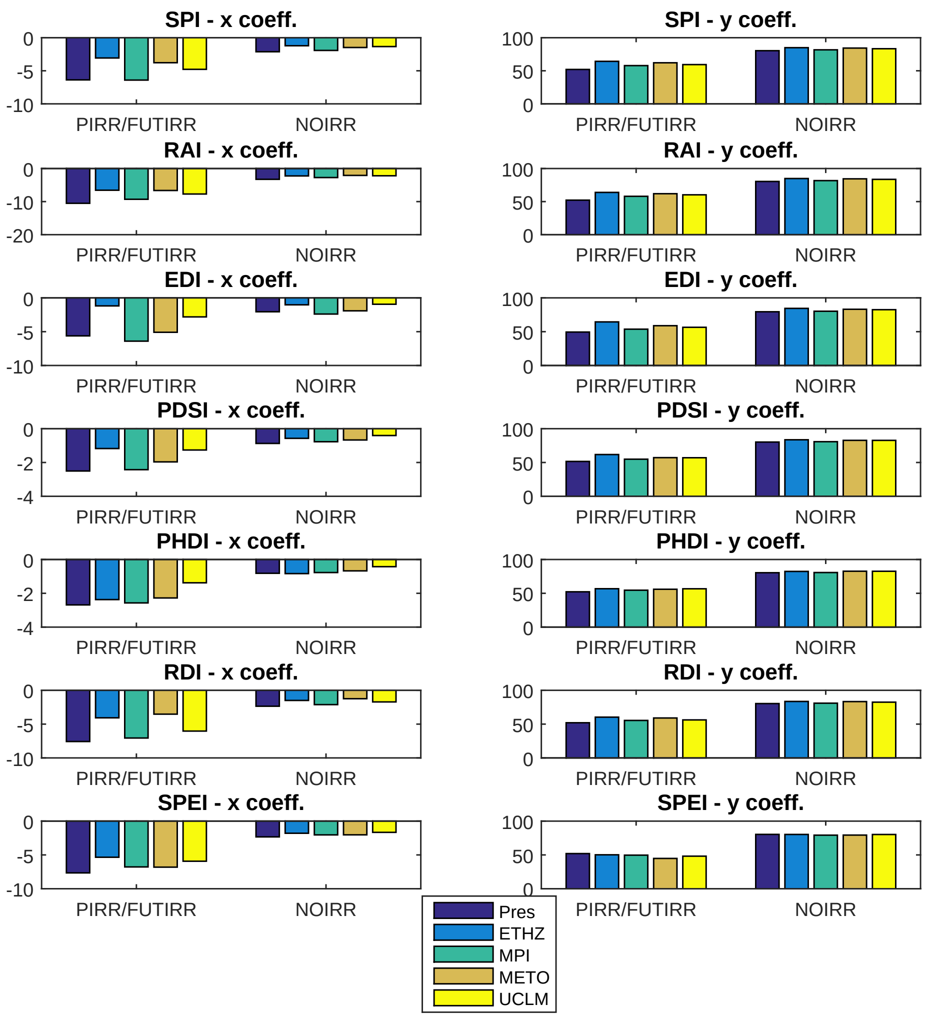

Figure 3: Coefficients of the linear regression of water deficit and drought indices for the present climate and the four climate scenarios.

2 Responses to the comments of reviewer 2

The modifications related to the comments of the second reviewer are highlighted in red in the manuscript.

1. **However, giving details ended up with a long Methods Sections. As seen, the Methods Section (Section 2) consists of 9 pages of the 19-page paper. Hence, one of the recommendation is moving the whole sub-parts of "Drought Indices (2.6.X)" in the Appendix.**

   We have moved this paragraph to the appendix and we now only give a short introduction to the selected drought indices in Section 2.6. The length of the Section 2.6 (now Section 2.4) was 82 lines in the original paper. It is now reduced to 30 lines.

2. **These are my recommendations, the authors may (or not) follow these:**

   - **The formula of the Penman-Monteith equation may be given in the Appendix.**
   - **I am not sure how much do we need the details of the Person's correlation coefficient. If the authors want to give it, it may be given in the Appendix.**

   We have added the Penman-Monteith equation to the appendix (Section 2 of the appendix). We have also shortened the paragraph on the Pearson's correlation coefficient (from 15 lines to 9 lines in the revised version). However, we did not move it to the appendix because of the importance of the Pearson coefficient in this paper.

3. **I was curious about the current irrigation usage, and noticed that the irrigation usage is enormous. The irrigation from the Aragon River collected at the Yesa reservoir in 2011 is 2* 10^6 m^3. Size of the irrigated portion is 3.54 km^2 from von Gunten et al. (2015). Hence the irrigation depth is 593 mm. On top of this number, mean annual precipitation (MAP) is 400 mm. The runoff, from Figure 6, with SPEI, is 2-3 m^3/s which is equivalent to 23-35 mm for the entire basin. If I assume no deep drainage from irrigation, water usage is roughly 1,000 mm per year. This number intrigued me in a lot. First, is this irrigation sustainable over the long-term period? 600 mm of irrigation within a 400 mm of MAP environment makes the farmers, the ecosystem very dependent on this irrigation, or headwater sources, the Pyrenees. Secondly, this value seems somewhat upper limit for maximum irrigation. Because the ecosystem is approaching**

towards the PET which is 1300 mm. Another saying from water-limited to energy-limited. I am not sure whether or not the authors agree with me, but I definitely encourage the authors write a few sentences into the Conclusion or the Discussion part about the sustainability of this current land-cover transformation. The demand for water due to PET changes of future climate (as seen drier outcomes of ETHZ) is much less significant than those of current land-cover transformation.

Studying the impacts of the irrigation onset is a major topic of the current research in the Lerma catchment. It is obviously a very political, sensitive, and important issue, even if it is somewhat outside of the scope of this paper. We entirely agree that the impact of land-cover transformation has more impact locally than the impacts due to climate change (e.g., von Gunten et al., 2015). We also agree that deep drainage is usually small. Hence, the agriculture in the Lerma (and in the Bardenas region in general) depends on irrigation, and therefore on the headwaters from the Pyrenees. Moreover, the percentage of irrigated land is expected to further increase in the region and the Yesa reservoir is being modified to store more water. Hence, the regional agriculture will very strongly depend on the availability of irrigation water in the future. Is this sustainable? It largely depends on the future hydrologic conditions in the Pyrenees, particularly in the catchment of the Yesa reservoir, and on our estimation of the ecological need of the Aragon River (from which the irrigation water is diverted). However, in any case, irrigation in the future will need to be appropriately planned, and farmers will have to adapt, for example by changing the type of crops or by upgrading to more efficient irrigation systems. Hence, the sustainability of the system is questionable from our point of view. We have added a short comment on irrigation management at the end of the conclusion (P18, L12-13). But it would deserve a more in-depth discussion, which would be outside of the subject of this particular paper.

4. **P4. L5. Wording. I recommend forcing only for meteorology.**

   This has been modified on P4, L5.

5. **P8. L17. Please cite"Table 1" before citing"Table 2". It may be good to cite"Table 1" in Section 2.1. Or you may reorder the Tables.**

   We now refer to Table 1 in the introduction in P3, L25.

6. **P19. L10. Please change ...project is' to ...project are'. Data may use as a singular or plural, however in two previous sentences you used as plural, hence to ensure consistency.**

   This has been modified on P18, L17.

7. **Figure 6. Can you ensure the y-scale similar for both figures? I think the limits are [0 0.08] or [0 0.07]. And definitely, y-value (discharge) must be truncated at zero. Morevoer, it needs a better colour selection.**

   Figure 6 has been modified as proposed.

References

Kirono, D., Kent, D., Hennessy, K., and Mpelasoka, F. *Characteristics of Australian droughts under enhanced greenhouse conditions: Results from 14 global climate models,* J. Arid Environ., 75, 566-575, 2011

Kumar, R., Musuuza, J. L., van Loon, A. F., Teuling, A. J., Barthel, R., Broek, J., Mai, J., Samaniego, L., and Attinger, S.. *Multiscale evaluation of the standardized precipitation index as a groundwater drought indicator*, Hydrol. Earth Syst. Sci. , 20, 1117-1131, 2016

Park, C.-K., Byun, H.-R., Deo, R., and Lee, B.-R. *Drought prediction till 2100 under RCP 8.5 climate change scenarios for Korea*, J. Hydrol., 526, 221-230, 2015

von Gunten, D., Wöhling, T., Haslauer, C., Merchán, D., Causapé, J., and Cirpka, O.A. *Estimating climate-change effects on a Mediterranean catchment under various irrigation conditions*, J. Hydrol. Reg. Stud., 4, 550-570, 2015.

Using an integrated hydrological model to estimate the usefulness of meteorological drought indices in a changing climate

Diane von Gunten[1], Thomas Wöhling[1,2,3], Claus P. Haslauer[1], Daniel Merchán[4], Jesus Causapé[4], and Olaf A. Cirpka[1]

[1]University of Tübingen, Center for Applied Geoscience, Hölderlinstr. 12, 72074 Tübingen, Germany
[2]Technische Universität Dresden, Department of Hydrology, Bergstr. 66, 01069 Dresden, Germany
[3]Lincoln Agritech Ltd., Ruakura Research Centre, Hamilton, New Zealand
[4]Geological Survey of Spain – IGME, C/ Manuel Lasala no. 44, 9B, Zaragoza, 50006, Spain

Correspondence to: Olaf A. Cirpka (olaf.cirpka@uni-tuebingen.de)

Abstract. Droughts are serious natural hazards, especially in semi-arid regions. They are also difficult to characterize. Various summary metrics representing the dryness level, denoted drought indices, have been developed to quantify droughts. They typically lump meteorological variables and can thus directly be computed from the outputs of regional climate models in climate-change assessments. While it is generally accepted that drought risks in semi-arid climates will increase in the future, quantifying this increase using climate model outputs is a complex process which depends on the choice and the accuracy of the drought indices, among other factors. In this study, we compare seven meteorological drought indices that are commonly used to predict future droughts. Our goal is to assess the reliability of these indices to predict hydrological impacts of droughts under changing climatic conditions at the annual time scale. We simulate the hydrological responses of a small catchment in northern Spain to droughts in present and future climate, using an integrated hydrological model, calibrated for different irrigation scenarios. We compute the correlation of meteorological drought indices with the simulated hydrological times series (discharge, groundwater levels, and water deficit) and compare changes in the relationships between hydrological variables and drought indices. While correlation coefficients linked with a specific drought index are similar for all tested land-uses and climates, the relationship between drought indices and hydrological variables often differs between present and future climate. Drought indices based solely on precipitation often underestimate the hydrological impacts of future droughts, while drought indices that additionally include potential evapotranspiration sometimes overestimate the drought effects. In this study, the drought indices with the smallest bias were: the rainfall anomaly index, the reconnaissance drought index, and the standardized precipitation evapotranspiration index. However, the efficiency of these drought indices depends on the hydrological variable of interest and the irrigation scenario. We conclude that meteorological drought indices are able to identify years with restricted water availability in present and future climate. However, these indices are not capable of estimating the severity of hydrological impacts of droughts in future climate. A well-calibrated hydrological model is necessary in this respect.

1 Introduction

In semi-arid regions, droughts are a serious natural hazard, often causing tens of millions of euros of damage (Gil et al., 2011). In northern Spain, for example, drought severity has increased in the last decades (Hisdal et al., 2001) and is expected to increase further in the next 50 years (e.g., Bovolo et al., 2010; Graveline et al., 2014; Majone et al., 2012), as a result of the ongoing increase in global mean temperature (e.g., Meehl et al., 2007). More severe droughts will negatively impact the region, notably the agricultural sector (Stahl et al., 2015).

Droughts have a wide range of impacts, and are often difficult to define. They have been classified in four main categories (Mishra and Singh, 2010; Samaniego et al., 2013; Wilhite and Glantz, 1985):

- *meteorological* droughts defined by a lack of precipitation over a certain period of time for a certain region,
- *hydrological* droughts defined by a reduced surface and subsurface water availability for a given water resource,
- *agricultural* droughts defined by a period of declining soil moisture and reduced crop yields,
- and *socio-economical* droughts defined by a failure of water-resources management to meet the supply and demand of water (taken as an economic good).

In order to quantitatively describe drought levels, about 150 different drought indices have been developed (Zargar et al., 2011). A drought index is a scalar composed of one or more measured variables affected by dry and wet periods. In the case of meteorological drought (which is the focus of this study), typical variables considered for the calculation of drought indices are precipitation and potential evapotranspiration.

In addition to the identification of drought periods, these meteorological drought indices are also good indicators for various droughts impacts in present climate, based on the results of a range of studies. For example, text-recollections of droughts, such as newspaper articles, are linked with different drought indices, indicating a relationship between the social impacts of droughts and drought-index values (Bachmair et al., 2015). Crop yields are also correlated with drought indices in different climatic regions (e.g., Quiring and Papakryiakou, 2003; Mavromatis, 2007). Moreover, Vicente-Serrano et al. (2012) analyzed the correlation between six drought indices and environmental variables, such as stream flow, tree rings widths, and soil moisture. A significant correlation between the studied environmental variables and the drought indices was found. The correlation between groundwater levels and drought indices seems to be smaller than for other drought impacts, but it was still noticeable (Kumar et al., 2016).

Hence, meteorological drought indices are correlated with hydrological and agricultural impacts of meteorological droughts. Consequently, they are also correlated with hydrological or agricultural droughts. Many of the drought impacts cited above, such as changes in groundwater levels or discharge, could also be conceptualized as an indicator of hydrological or agricultural droughts. For example, groundwater levels could be transformed to a drought indicator such as the standardized groundwater level index (SGI, Bloomfield and Marchant (2013)) to identify hydrological droughts (Kumar et al., 2016). Indeed, hydrological impacts of droughts and hydrological drought indices are often two perspectives of the same drought event. The viewpoint of this study is that changes in environmental variables are introduced by non-stationary meteorological forcing, i.e., that hydrological changes are a consequence of meteorological droughts. Therefore, we will not use hydrological variables to define droughts.

The relationship between meteorological drought indices and drought impacts is valid for many drought indices in present climate, including simpler indices using one input variable, such as precipitation. However, the suitability of drought indices has not been tested under a changing climate. The ongoing increase in air temperature was not taken into account. Because climate change will probably impact drought intensity and frequency (e.g., Dai, 2011), various studies have aimed at predicting future changes in dry periods using drought indices based on the output of regional or global climate models. An assumption of these studies is that drought indices perform similarly in present and future climate. Our aim is to test this hypothesis. That is, we will test the capability of meteorological drought indices to predict hydrological impacts of droughts in a changing climate.

A large number of drought indices have been used in recent climate-impact studies. For instance, the standardized precipitation index was often used to study future droughts (e.g., Leng et al., 2015; Masud et al., 2015; Tue et al., 2015; Zarch et al., 2015). However, several studies used other indices, as the reconnaissance drought index (e.g., Kirono et al., 2011; Zarch et al., 2015), the standardized precipitation evapotranspiration index (e.g., Kim et al., 2014; Masud et al., 2015), the effective drought index (e.g, Park et al., 2015), or the Palmer drought severity index (e.g., Burke et al., 2006), among others. The choice of the drought index can have an important impact on the results. For example, Kim et al. (2014) and Park et al. (2015) predicted future droughts over Korea in the next century using very similar climate scenarios. While Kim et al. (2014) projected an increase in the severity of droughts in this region, Park et al. (2015) projected a more complex spatial pattern and a possible decrease in drought severity in coastal regions. A possible reason for these contradictory results is that Park et al. (2015) used a drought index based on precipitation only, while Kim et al. (2014) used an index which considers both potential evapotranspiration and precipitation. Precipitation-based drought indices, such as the effective drought index (EDI) or the standardized precipitation index (SPI), tend to work well in present climate. However, they may be inadequate to predict climate-change effects because they neglect the increase in potential evapotranspiration, resulting in a possible under-estimation of the intensity of future droughts (Dubrovsky et al., 2009; Vicente-Serrano et al., 2009, 2015; Zarch et al., 2015).

To study the validity of drought indices in future climate, we chose seven well-known drought indices (Table 1), which can be computed from the output of climate models, such as precipitation, temperature or potential evapotranspiration. We investigate the ability of these indices to predict hydrological variables under drought conditions: groundwater heads, discharge at the catchment outlet, and water deficit of the crops, under present and (projected) future climate conditions. These three metrics address different hydrological effects of droughts of high ecologic and/or economic relevance. Reduced stream discharge can deteriorate the ecological status of the stream because the stream temperature and the concentrations of contaminants increase with decreasing discharge. In the most extreme case, the stream falls dry. The drawdown of groundwater heads is of high economic relevance when groundwater is pumped for water supply and irrigation which, however, is not the case in the studied catchment. Groundwater levels also control low flows in gaining streams. Finally, the water deficit of the crops, that is, the difference between transpiration under conditions when enough water is available and the actual transpiration, is a simple metric of water stress experienced by the crops, which may diminish crop yields.

A fully-integrated hydrological model of a small catchment, the Lerma catchment, in north-east Spain, is used to simulate the hydrological responses to the meteorological forcing. This catchment has recently undergone a monitored transition from rainfed to irrigated agriculture, in which the irrigation water is imported from the Yesa reservoir located outside of the catchment (Merchán et al., 2013). The model was calibrated under different irrigation conditions (von Gunten et al., 2014), which increases our confidence in its ability to predict the hydrological responses to changes in meteorological forcing and land-use. We use these different land-use/irrigation schemes to test the different drought indices. The outputs from a weather generator, representing present and future climate, are used as meteorological inputs to the model and for the computation of the drought indices.

The remainder of this paper is structured as follows: First, we present the methodology used in this study. Specifically, we briefly describe the study area, the hydrological model, the drought indices, and the methods used to compare them. Secondly, we discuss the climate and the irrigation scenarios. We also compare the frequency distribution of drought indices computed from measurements and based on the outputs of the weather generator. Next, we summarize an analysis of the correlation coefficients between hydrological variables and drought indices for two different land-uses (with/without irrigation), and for present and future climate scenarios. Afterwards, we investigate changes in the relationship between these drought indices and the hydrological variables. We then use these results to predict relevant changes in drought risks in the study area in future climate. Finally, we discuss the usefulness of drought indices in climate-impact studies.

2 Methods

2.1 Overview

The main objective of this paper is to test the suitability of several meteorological drought indices to estimate the impacts of climate change on the water cycle of a small catchment. Seven drought indices, described in Sect. 2.4 and in the supplementary material, are investigated. The information on drought severity (as computed by these indices) is compared to three simulated hydrological impacts of drought: (1) the mean annual discharge at the outlet, (2) the mean annual hydraulic heads in 12 observations wells of the local aquifer, and (3) the water deficit (WD), which is a simplified representation of how well the water demand of the crops can be met (Abrahao et al., 2011):

$$WD\,[\%] = 100 \times \frac{ET_c - AET}{ET_c} \tag{1}$$

where ET_c is the annual crop evapotranspiration under standard conditions (Allen et al., 2000), and AET is the simulated actual evapotranspiration, calculated on the yearly time scale.

The time series of the drought impacts listed above are obtained using the outputs from a calibrated, integrated, pde-based, hydrological model (Sect. 2.3) forced by present and future meteorological time series (Sect. 3.1), and daily irrigation scenarios (Sect. 3.3). Five climate scenarios (one based on present climate and four based on the projections of regional climate models) and three irrigation scenarios are constructed and combined with each other in our simulations. The length of the simulation is 180 years for each combination of (present and future) climate and irrigation scenarios. This is equivalent to a total 2700 simulated years. From these 2700 simulated years, we extract time series of discharge, hydraulic heads, and water deficit.

These time series are directly used to represent the drought impacts on hydrology. They are compared to the time series of meteorological drought indices (Sect. 2.5): We first compute the Pearson correlation coefficient between the drought indices and the hydrological variables. Next, we analyze changes in the (assumed) linear relationship between hydrological variables and drought indices. These comparisons are repeated in present and future climate for the different irrigation scenarios. A suitable drought index for climate-change studies would have a large correlation coefficient with all hydrological variables and the relationships between this index and the hydrological variables would be identical in present and future climate. The results and the interpretation of these quantitative studies are presented in Sect. 4 and Sect. 5.

This study is focused on annual droughts. We choose the annual time scale because it is often used when predicting future droughts (e.g., Kirono et al., 2011; Park et al., 2015) and because it is the most dominant precipitation cycle worldwide (Park et al., 2015). Even though seasonal and sub-annual time scales are essential for drought management (e.g., Kumar et al., 2016), we aim here to test the capabilities of drought indices to predict future hydrological impacts, not to produce direct predictions of future drought impacts. For our purpose, annual time scale is sufficient and enables a detailed analysis of the differences between the correlation coefficients and the linear relationships, which are at the center of this study.

2.2 Study area

The Lerma catchment is situated within the Ebro basin in Spain with an altitude varying between 330 and 490 masl., and an area of ~7.3 km^2 (Fig. 1). Its climate is classified as semi-arid, with a mean precipitation of ~400 mm/year (2004-2011) and a mean potential evapotranspiration rate of ~1300 mm/year (2004-2011) (Merchán et al., 2013). Precipitation and temperature have been measured since 1988 at the meteorological station of Ejea de los Caballeros (~5 km north of the study area). Radiation, wind, and relative humidity have been measured since 2003. Annual precipitation is highly variable, ranging from 268 mm/year to 558 mm/year (2004-2011). Because of the limited water resources, drought is a serious natural hazard in the region (Bovolo et al., 2010).

The catchment underwent a rapid transition from non-irrigated to irrigated agriculture between 2006 and 2008. The majority of the fields within the catchment are now irrigated, with an irrigation water volume of $2.1 \cdot 10^6$ m^3 in 2011 (Merchán et al., 2013). This transition was closely monitored and monthly hydraulic head data, daily discharge, crop types, and daily irrigation volume are available. In addition, a vertical-electrical-sounding campaign (Plata-Torres, 2012) was conducted to better understand the local geology. Two main hydrologically relevant layers were identified: The top layer is composed of clastic and unconsolidated Quaternary deposits and forms a shallow aquifer. Underneath lies an aquitard composed of lutite and marlstones (Fig. 2). Soils are relatively shallow, with depths below ground surface ranging between 0.3 and 0.9 m (Beltrán, 1986), and are classified as inceptisols.

2.3 Hydrological model

To simulate the hydrological response of the Lerma catchment, we use HydroGeoSphere (Therrien, 2006), a three-dimensional, fully-coupled, integrated hydrological model, based on partial differential equations. In HydroGeoSphere (Therrien et al., 2010), water flow in the variably-saturated sub-surface is modelled using the three-dimensional Richards' equation, while overland flow is simulated by the diffusive-wave approximation of the Saint-Venant equations. We use the Mualem-van Genuchten parametrization (van Genuchten, 1980) to relate relative permeability and water saturation to capillary pressure in the vadose zone. The surface and subsurface domains are coupled using a dual-node approach, where the coupling between the domains is conceptualized as a virtual thin layer of porous material. Potential evapotranspiration is computed using the FAO Penman-Monteith equation (Allen et al., 2000), and time-varying crop coefficients are used to account for the spatial variability of crops (see the supplementary material for more information). The model choice is based on the necessity to model the transition to irrigation, which has a large impact on the hydrology of the catchment. Moreover, HydroGeoSphere allows to simultaneously study the impact of droughts on the surface and subsurface components of water flow. The underlying equations have been reviewed by von Gunten et al. (2014, 2015) and are not repeated here.

The conceptual model of our study area and its calibration have also been presented by von Gunten et al. (2014) and thus are only presented here briefly. We divide the sub-surface catchment in six zones, two zones representing the aquitard, one representing the aquifer, and three representing the different soil zones (Fig. 2). The model parameters are homogeneous in each zone and the saturated hydraulic conductivity is one order of magnitude smaller in the vertical direction than in the horizontal one. The surface domain is divided into 55 zones, representing the different farm fields. Daily irrigation volume, Manning's parameters, seasonal leaf area index, and rooting depth are specified separately for each surface zone, based on crop types and irrigation data. Precipitation is given as daily input, apart from days with intense rainfall (>25mm/day). In this case, precipitation data is given as a 3-hour mean during summer and spring, and as a 9-hour mean during autumn and winter, to mimic intense convection events (von Gunten et al., 2014), which are frequent in the region. A no-flow boundary condition is assumed at the lateral and the bottom boundaries of the sub-surface domain. Critical flow depth is used for the lateral boundaries of the surface flow domain.

We calibrated the parameters of the model using three computational grids of increasing resolution (von Gunten et al., 2014). The calibrated parameters are the hydraulic conductivity in all zones, apart from the "weathered aquitard" zone (Fig. 2), the porosity of the aquifer, and the van-Genuchten parameters of the soil zones. The calibration period is from 2006 to 2009 and the validation period is from 2010 to 2011. The model is calibrated on the measured discharge at the outlet and on the hydraulic heads in eight observation wells (twelve observation wells were used during validation). The model reproduces the measurements satisfactorily (von Gunten et al., 2014). For example, the Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970) of discharge is of 0.74 during the calibration period and of 0.92 during the validation period. The model performs similarly well under all irrigation conditions. Because the model was able to reproduce the response in both discharge and groundwater tables to the changes in irrigation practice, we are confident that it can also predict the response to changes in meteorological forcing projected by climate models.

2.4 Drought indices

More than 150 drought indices have been developed in the past (Zargar et al., 2011) and it would be unrealistic to include all of them in this study. Therefore, we have selected seven well-known and commonly-used drought indices, based on the reviews by Agwata (2014), Hayes and Lowrey (2007), Heim (2002), Niemeyer (2008), and Zargar et al. (2011). Our choice was guided by the required data input and the popularity of the indices in recent studies related to climate change. The selected indices are:

- the standardized precipitation index (SPI): SPI (McKee et al., 1993; Svoboda et al., 2012) is a widely-used drought index whose computation is based on fitting long-term precipitation data to a probability distribution. This probability distribution is then transformed into a normal distribution.

- the standardized precipitation evapotranspiration index (SPEI): The computation of SPEI (Vicente-Serrano et al., 2009) is similar to SPI. However, the difference between precipitation and potential evapotranspiration is used rather than only precipitation.

- the rainfall anomaly index (RAI): RAI (e.g., Keyantash and Dracup, 2002) represents a ranking of annual precipitation, compared to the most negative precipitation anomalies recorded.

- the effective drought index (EDI): EDI (Byun and Wilhite, 1999) is a drought index computed using daily precipitation to account for the effect of precipitation variability on droughts.

- the Palmer drought severity index (PDSI) : PDSI is a widely used drought index which was developed to measure the cumulative departure of moisture supply during dry periods(Palmer, 1965).

- the Palmer hydrological drought index (PHDI): PHDI is an index similar to PDSI, which was developed to better represent hydrological droughts (Palmer, 1965).

- the reconnaissance drought index (RDI): The computation of RDI (Tsakiris and Vangelis, 2005) is based on the FAO aridity index, i.e., the ratio of precipitation and potential evapotranspiration.

We present the selected indices in more detail in the supplementary material and provide a summary in Table 1. We generally consider meteorological drought indices that aggregate data annually (Section 2.1). The only exceptions are the Palmer drought indices (PDSI and PHDI) whose time length depends on an empirical estimation of the start and the end of drought periods (Szép et al., 2005).

Potential evapotranspiration (ET_0) is needed to compute SPEI, PDSI, PHDI, and RDI. To obtain this variable, we use the FAO Penman-Monteith equation (Allen et al., 2000), which is presented in the supplementary material along with additional explanations on the calculation of ET_0.

2.5 Methods of comparing the drought indices to predict hydrological variables

To compare how well the drought indices can predict the chosen hydrological variables in present and future climate, we use two approaches. First, we compute the Pearson's linear correlation coefficient r, which quantifies how well the variability in one time series can be explained by the variability of another time series, assuming a linear relationship between the two variables. In the context of this study, it indicates if the drought indices have the capability of finding periods with a discharge or hydraulic heads lower than usual and periods with water deficit higher than usual. It is defined as follows:

$$r = \frac{cov(DI, x)}{\sigma_{DI}\sigma x} \tag{2}$$

in which cov is the covariance, σ_i is the standard deviation of the variable i, DI is the value of the drought index and x is the hydrological variable under consideration.

The Pearson's correlation coefficient indicates the degree of linear dependence between two variables. However, if this correlation coefficient is calculated under different climatic conditions, it does not indicate possible changes in the coefficients of the (assumed) linear dependencies. To investigate the changes in the linear dependency between the two climates, we perform a linear regression between a drought index and a hydrological variable in the present climate. Then, we use this linear relationship to predict the hydrological variables from the same drought indices in future climate. We conduct this analysis for each combination of drought index and hydrological impact in all irrigation scenarios. By this, we aim to investigate if drought indices in future climate represent on average a similar drought (i.e., a drought with similar hydrological impacts) than in present climate. This is important because many drought studies (e.g., Kirono et al., 2011) only report changes in drought indices, implicitly assuming identical drought impacts for identical drought-index values in present and future climate. However, a drought described by a SPI-value of -1, for example, may have different consequences on discharge and water deficit in projected future climate than under current climate conditions (see Sect. 4.2).

To quantify the changes in the linear dependencies between hydrological variables and drought indices, two performance metrics were selected: The relative model bias B_{rel} and the normalized root mean square error ($NRMSE$). The relative model bias is the sum of the differences between the predicted and the actual values of the hydrological variable, divided by its mean value.

$$B_{rel} = \frac{100\%}{\frac{1}{n}\sum_{i=1}^{n} V_{mod,i}} \sum_{i=1}^{n} (V_{stat,i} - V_{mod,i}) \tag{3}$$

in which $V_{stat,i}$ indicates the predicted value of discharge or water deficit based on the linear regression, $V_{mod,i}$ represents the value of the same variable predicted by the hydrological model and n is the length of the time series.

The $NRMSE$ is the root mean square error divided by the standard deviation of the least-square regression in present climate σ_{pres}:

$$NRMSE = \frac{1}{\sigma_{pres}} \sqrt{\frac{\sum_{i=1}^{n} (V_{stat,i} - V_{mod,i})^2}{n}} \tag{4}$$

In present climate, the variability of the differences between the outputs from the hydrological model and the linear regression is smaller than 12% of the average difference between model outputs and the linear regression. Hence, the error of the linear model in the present climate can be considered homoscedastic, i.e, σ_{pres} is considered constant in the subsequent analysis.

3 Climate and irrigation scenarios

3.1 Climate scenario

The climate scenarios used in this study have been presented by von Gunten et al. (2015) and are thus only summarized here.

Our future climate scenarios cover the time period of 2040-2050, using the A1B IPCC emission scenario (Nakićenović et al., 2000). They are based on 4 regional climate models from the ENSEMBLES project (van der Linden and Mitchell, 2009) driven by two global climate models (Table 2). As it is not advisable to use the direct outputs from climate models as input for a small-scale hydrological model (Prudhomme et al., 2002), we have downscaled the outputs from the climate models using a weather generator, i.e., a statistical model reproducing the characteristics of the observed climatic time series (Srikanthan and McMahon, 2001). We calibrated the weather generator using the observed time series of the closest meteorological station (Ejea de los Caballeros). Then, the parameters of the weather generator were modified using the differences between the control and future simulations of the regional climate models. These change factors, described in Burton et al. (2010), are an indication of future changes of the mean and variability of precipitation, temperature, radiation, and relative humidity. The weather generator is run using the updated parameters to create the future climate scenarios. In this study, we use the RainSim weather generator for precipitation (Burton et al., 2008) and the EARWIG weather generator for ET_0 (Kilsby et al., 2007).

The chosen downscaling procedure has the advantage of producing longer time series, compared to the relatively short (23 years) climate record in the Lerma catchment. Moreover, it reproduces future changes in the precipitation variability, and not only in the precipitation mean, which is an important criterion when studying future droughts.

Nevertheless, the downscaling of climate model outputs is a complex task and the choice of a particular downscaling method can have a large impact on the results (Holman et al., 2009). Our study is not an exception and the downscaling process presented here might introduce uncertainties in the climate scenarios. We have mitigated this issue using three different approaches: a) We prepared both present and future time series of meteorological inputs using the weather generator. Hence, the potential bias resulting from the weather generator is reproduced in the present and future time series. b) We compared the future time series of precipitation and ET_0 downscaled with the weather generator with the corresponding time series downscaled with a simpler bias correction method (Li et al., 2009). The time series were found to be generally similar regardless of the downscaling method (von Gunten et al., 2015). c) The time series of present precipitation and ET_0 have been extensively tested against measurements to control the quality of the weather generator outputs (von Gunten et al., 2015).

3.2 Reproduction of the drought indices by the weather generator

In addition to the reproduction of the meteorological forcing mentioned in Sect. 3.1, the weather generator should also reproduce the frequency distribution of the studied drought indices. Here, we compare these frequency distributions in the observed climate record with the corresponding frequency distribution computed from the weather generator outputs in the current climate.

All seven drought indices used in our study are normalized (Sect. 2.4) so that they can be used in different regions. If the normalization would have been carried out separately in the observed and simulated data, the frequency distributions of the drought indices would be similar, regardless of the similarity of the time series. To provide a meaningful comparison, we compute the normalization on the simulated data (weather generator) and we use the same normalization for the observed data (current climate record).

To compute each drought index, we use the measured time series, which has a length of 23 years (1988-2011). In addition, we compute the drought indices using the simulated data. To get a comparable length between measured and modeled data, the time series of drought indices based on the weather generator are separated into 15 periods with a duration of 23 years each (totaling 354 years). The final length of this time series is chosen such that it is about twice the length of the hydrological simulations (180 years). We then prepare 15 empirical cumulative distribution functions (*ecdf*) based on the outputs of the weather generator and compare them with the *ecdf* based on the current observed climate record (Fig. 3).

The *ecdf* of all drought indices based on measurements fall into the region defined by the 15 modeled *ecdf*. Hence, differences between the observed and simulated data were small, compared to the difference between the 15 modeled *ecdf*. In addition, we used a 2-sided Kolmogorov-Smirnov test to compare the time series based on modeled and measured data. This test (e.g., Hazewinkel, 2001) is a non-parametric statistical test which quantifies the maximum distance in cumulative probability between two distributions and tests how likely it is that the two samples are drawn from the same distribution. All drought indices pass this test, i.e., the null hypothesis of identical *ecdf* between measured and simulated data is not rejected at a 5% significance level. Therefore, the drought indices based on the time series of the weather generator outputs are showing a reasonable agreement with the observed time series to be used in present climate. Weather generators are commonly operated to produce time series of future hydro-meteorological variables (e.g., Burton et al., 2010) and we are also confident to use the weather generator to produce future time series of drought indices.

3.3 Irrigation scenarios

Consistent with our earlier study (von Gunten et al., 2015), we use three irrigation (or land-use) scenarios that can be summarized as follows:

- scenario NOIRR: without irrigation and without agriculture.
- scenario PIRR: with present cropping patterns and present irrigation.
- scenario FUTIRR: with present cropping pattern, but with an updated irrigation volume to account for future climatic conditions. To create this scenario, we assume that the irrigation efficiency will not change in future climate. In addition, we assume that the increase in irrigation will only depend on the increase in ET_0 and changes in precipitation amount (see Toews and Allen, 2009).

The irrigation water originates from the Yesa reservoir, which is situated about 65 km north of the catchment, at the foot of the Pyrenees mountains. The modeled increase in the future irrigation volume is between 6.6% and 10.6% of the present irrigation volume, depending on the climate scenario. Water availability in the reservoir is not considered to be a limiting factor in this study.

3.4 Predicted climatic change

Future precipitation (Fig. 4) is predicted to decrease in summer and spring (between 3% and 39% of the current precipitation, depending on the regional climate model). In winter and autumn, an increase in precipitation is predicted (between 1% and 55%). Change in total annual precipitation depends on the regional climate model. MPI and UCLM predict a wetter future, while ETHZ and METO predict a dryer one (see Table 2 for the references of the regional climate models). The coefficients of variation increase in spring (between +3% and +6%), decrease in winter and autumn (between -0.1% and -10%), and do not show a clear trend in summer (between +5% and -5%).

Because of the higher temperature, potential evapotranspiration (ET_0) increases (between 9% and 22% in the annual average) in all regional climate models for all months. This increase might impact droughts, regardless of the precipitation changes.

3.5 Modeled catchment responses to climate change

The hydrological responses of the Lerma catchment to climate change under different irrigation conditions have been modelled previously by von Gunten et al. (2015). As this study extends these results, we will shortly recall them here. Overall, the catchment responses to climatic change strongly depend on the irrigation scenarios and on the considered regional climate model. For all considered climate scenarios, the increase in temperature and the decrease in summer precipitation result in a lower groundwater table and in a decrease of low-flow discharge (defined as the total discharge during dry periods). This decrease is more intense in scenarios with irrigation than in the scenario without irrigation. Peak discharge decreases if irrigation is present. However, it often increases in scenarios without irrigation, notably because the dryer soil results in lower infiltration during thunderstorms. Spring and summer actual evapotranspiration increases if the catchment is irrigated because of the increase in ET_0 and the relatively large soil moisture. Without irrigation, changes in annual actual evapotranspiration depend on the annual precipitation. In climate scenarios where precipitation decreases, actual evapotranspiration decreases because of the lower water availability. On the contrary, if annual precipitation increases, actual evapotranspiration also increases. More details on the modelling of hydrological impacts of climate change are available in von Gunten et al. (2015).

4 Results

4.1 Correlation coefficients between drought indices and hydrological variables

In this section, we analyze the correlation between the different drought indices for the 180 years of each scenario and the corresponding simulated mean annual discharge, water deficit, and hydraulic heads. For this purpose, we use the Pearson's linear correlation coefficient r between the drought indices and the hydrological variables (Sect 2.5). We conduct the same analysis for present and future climate, and for the different irrigation scenarios. Here, we present only the main results of this comparison (details are available in the supplementary material).

The values of the correlation coefficients between the hydrological variables and the drought indices depend on the drought indices. For example, the correlation coefficient between water deficit and EDI is 0.47, while the correlation coefficient between this variable and RAI is 0.78 in the present climate. However, the correlation coefficients for a particular drought index and a particular hydrological variable are similar for all irrigation scenarios in present and future climate. For example, let us consider the correlation coefficients between drought indices and discharge (Fig. 5). In present climate, SPEI, RDI, and RAI have the highest correlation with discharge in the PIRR scenario ($0.77 < r < 0.80$) as well as in the NOIRR scenario ($0.81 < r < 0.83$). These indices also have similar correlation coefficients in future climate ($0.79 < r < 0.84$). If we consider the correlation of a particular drought index with discharge over all climate/irrigation scenarios, the differences in r is < 0.1.

Water deficit exhibits a similar behavior as discharge when correlation coefficients are examined. When the absolute values of correlation coefficients are large in present climate, they will be similarly large in future climate or in another irrigation scenario. SPEI, RDI, and RAI have the largest correlation coefficients with water deficit in all scenarios ($0.78 < |r| < 0.81$).

Correlation coefficients between drought indices and groundwater heads in a particular observation well are similar for all drought indices considered. However, the correlation coefficients are very different from one observation well to another (see supplementary material for more information).

Seasonal differences in the correlation coefficients are not considered here, even though these correlations might be influenced by the annual cycle. Our analysis is focused on annual droughts.

4.2 Linear regressions between hydrological variables and drought indices

The previous section has shown that the linear correlation between drought indices and hydrological variables is relatively similar under all climatic and irrigation conditions. Hence, a particular drought index is able to identify the dry periods in present and future climate. However, this does not indicate whether the droughts in future climate have similar hydrological impacts than those in present climate. Correlation coefficients quantify how well a relationship between two variables can be expressed by an (assumed) linear equation, without considering the actual coefficients of the linear equation. The latter are commonly evaluated by linear regression.

Identifying changes in the regression coefficients of the relationships between drought-indices and hydrological variables is important when making hydrological predictions based on meteorological drought indices in a changing climate. Only when the regression coefficients do not change, the same value of a drought index has the same hydrological impact. Towards this end, we compare changes in the (assumed) linear regressions between drought indices, and discharge or water deficit (Sect. 2.5). In the subsequent analysis, we do not consider hydraulic heads because the results almost entirely depend on the position of the observation well.

The stability of the relationship between drought indices and hydrological variables strongly depends on the chosen drought index and the irrigation scenario. In Fig. 6, we exemplify the relationship between SPEI and discharge for two irrigation scenarios in present and future climate. On the lower panel of Fig. 6 (scenario FUTIRR), the relationship between SPEI and discharge is relatively stable in different climates. A drought with a similar intensity (as defined by SPEI) has similar impacts on discharge in present and future climate. On the top panel, the bias is larger. In this case, a drought with a particular SPEI-value results in a different annual mean discharge in present and future climate.

As outlined above, we use two different performance metrics to quantify this bias, the relative model bias B_{rel} and the $NRMSE$ (Sect 2.5). Fig. 7 shows these two metrics for all indices and the two hydrological variables. Overall, our results suggest that the relationships between the chosen meteorological drought indices and hydrological variables are not stable under a changing climate. The computed model biases between drought indices in present and future climate appear important. In the scenario without irrigation, the largest relative model bias is 86.7% for discharge and 3.8% for the water deficit (mean discharge in present climate: 0.015 m^3/s, mean annual water deficit: 80%). With irrigation, the largest relative bias for discharge is -25.2% for the RAI drought index and 14.2% for water deficit (mean discharge: 0.03 m^3/s, mean annual water deficit for irrigated and non-irrigated zones: 52%). In the worst case described above (discharge without irrigation), the relative model bias is on the same order of magnitude than the value of the hydrological variable, which is a significant difference. For certain conditions, however, the bias is low. For example, water deficit in the scenario without irrigation is predicted well by the linear model (the largest bias is equivalent to only 3.8% of the present water deficit).

For discharge, model bias depends strongly on the irrigation scenario (Fig. 7, top panels). With irrigation, the drought indices often underestimate the changes in discharge, especially if the indices are based on precipitation only. For example, in the case of SPI, the model bias for discharge is -24.8% with irrigation (and 6.8% without irrigation). On the contrary, drought indices which are based on ET_0 and precipitation have a lower bias in the scenario with irrigation than in the scenario without irrigation. For example, SPEI has a model bias of 86.7% with irrigation and of 11% without irrigation. In the Lerma catchment, discharge is more sensitive to climate change when irrigation is present (von Gunten et al., 2015). Hence, drought indices which are more sensitive to climate change, notably to changes in ET_0, predict changes in discharge better in irrigated cases. The discharge in the scenario without irrigation does not change significantly and drought indices with a smaller reaction to climate change are better predictors for hydrological impacts than those with a stronger reaction (Fig. 7, top panels).

For the water deficit (Fig. 7, bottom panels), drought indices which include ET_0 have a lower model bias than indices which only include precipitation. In the case of SPI with irrigation, the relative model bias is 13.9%. In the case of RDI, which includes ET_0, the model bias is 5.4%. The lower bias for drought indices containing ET_0 can be explained because ET_0 is directly influencing the water-deficit calculation. The relative model bias is lower in the scenario without irrigation than in the scenario with irrigation. Indeed, irrigation is not accounted for in the calculation of the drought indices, but it influences the modeled water deficit.

The drought indices with the lowest model bias and a correlation coefficient $r > 0.6$ are: RAI for discharge in NOIRR scenario, RDI for the water deficit in FUTIRR/PIRR scenario, and SPEI for the water deficit in the NOIRR scenario and discharge in FUTIRR/PIRR scenario.

4.3 Future droughts

In Sect. 4.1 and Sect. 4.2, we explored the relationships between the different drought indices and the selected hydrological variables in present and future climate. In the present section, we compare the drought indices in present climate to those in future climate. This is a step forward compared to previous studies because we use the information of Sect. 4.1 and Sect. 4.2 to improve the predictions of future droughts, notably to interpret differences between the predictions based on different drought indices.

Our definition of a drought is identical for present and future climate. Practically, we standardize the drought indices in the present climate and keep the same standardization (explained in Section 2.4 and in the supplementary material) in the future climate. From a conceptual point of view, this is unexpected as meteorological droughts can be defined as a period of exceptionally dry conditions. If the average precipitation changes, the definition of a meteorological drought should also be changed. However, from a practical point of view, drought severity depends on the water needs and on the vulnerabilities of society and agriculture. Hence, the definition of future droughts is linked to current conditions. From this perspective, using the same standardization in present and future climate is logical. Moreover, this procedure has been applied in the majority of studies on future droughts (e.g., Zarch et al., 2015).

Fig. 8 shows the changes between present and future climate in the seven drought indices based on the outputs of the four regional climate models. Note that a decrease in the values of the drought indices indicates an increase in drought intensity.

When we compare the changes in drought indices between present and future climate, significant differences can be observed between the different climate scenarios (based on the 4 regional climate models). Indices which only contain precipitation (RAI, SPI, and EDI) predict a small increase in droughts or a small decrease depending on the climate scenario (Fig. 8, top panels). For example, the average SPI decreases by -0.4 when using the ETHZ climate scenario and increases by 0.2 when using the MPI scenario (for comparison, an SPI of -3 would be an extreme drought). In these scenarios, the MPI and UCLM regional climate models predict an increase in annual precipitation for the Lerma catchment (von Gunten et al., 2015). Hence, the climate scenarios based on these regional climate models result in a decrease in drought events (i.e., an increase in the drought index value) when indices are only based on precipitation (RAI, SPI, and EDI). Indices which also consider ET_0 (Fig. 8, bottom panels) indicate an increase in droughts in all analyzed future climates. However, this increase is smaller when MPI and UCLM are used to construct the climate scenario. In the UCLM case, a decrease of 1.59 in the mean value of SPEI is computed. In contrast, when the ETHZ climate model is used, a decrease of 2.95 is computed (Fig. 8, bottom panel). Differences in the values of drought indices which include evapotranspiration between present and future climate follow predicted changes in ET_0. Models which predict a strong increase in ET_0, such as ETHZ, result in a stronger increase in drought risks. A change in the coefficient of variation of ET_0 or annual precipitation (von Gunten et al., 2015) is not directly related to changes in drought indices.

The sources of the differences between the climate scenarios, which result in the aforementioned differences in the values of drought indices, are uncertain. Nevertheless, two factors are often cited when discussing differences in future climate scenarios with identical emission scenarios: Modeling of cloud cover (van der Linden and Mitchell, 2009) and parameterization of the interactions between the land cover and the atmosphere (Flato et al., 2013). Both processes have a large influence on precipitation and evapotranspiration, and therefore on drought predictions.

In addition to the differences related to the chosen climate scenario, the choice of the drought index has a large influence on the prediction of future droughts. These differences in drought prediction are largely the reflection of the differences in the linear relationships between drought indices and hydrological variables discussed in Sect. 4.2. If a drought index has a negative bias for discharge (as it is the case for indices which are based on precipitation only), small changes in future droughts are predicted. For example, when we average the four different climate scenarios, mean RAI in future climate shows a decrease of 0.02 when compared to RAI in present climate (Fig. 8, top panel, left column). Based on the linear model under present irrigation conditions, this can be translated to an increase in water deficit of 0.21 mm/year and a decrease in discharge of 8.7×10^{-5} m^3/s. These changes are unlikely to have consequential impacts on irrigation or on the hydraulic regime of the catchment. For the indices that depend on ET_0, the predicted increase in droughts becomes larger. For example, mean SPEI shows a decrease of -2.43 (average of four regional climate models). If we would use the linear model developed in present climate, the decrease in discharge in the scenario with irrigation would be of 0.01 m^3/s, which is one third of the annual mean discharge. Based on the hydrological model, the change in discharge in the FUTIRR scenario is 0.006 m^3/s (average of the four climate models). Large uncertainties linked with climate prediction and hydrological modeling still prevail in this estimation. However, the hydrological model generally reproduces discharge and hydraulic head measurements. Moreover, it simulates many relevant processes leading to discharge generation. Hence, we assess this model to be more reliable in predicting hydrological effects of climate change than a mere comparison of meteorological drought-index values.

If we analyze the hydrological impacts of meteorological droughts (defined here as periods with an SPI- and a SPEI-value lower than one), the general behavior is similar in present and future climate (Figure 9). As expected, during droughts, precipitation and discharge decrease, and actual evapotranspiration increases. In present climate, in the scenario without irrigation, discharge decreases by more than 60% during dry periods when compared to the average conditions. In the scenario with irrigation, the decrease in discharge is less marked (24% difference between dry and average conditions) as the irrigation water partly compensates the lack of precipitation. On the contrary, impacts of droughts on actual evapotranspiration are stronger in the scenario with irrigation than in the scenario without irrigation. In the latter case, soil moisture is simply too low to support actual evapotranspiration, regardless of the evaporative demand (von Gunten et al., 2015). In future climate, the decrease in precipitation and the increase in ET_0 during droughts is more intense than in present climate (Figure 9). Hence, we could expect more intense droughts with larger hydrological impacts. If the catchment is irrigated, modeled hydrological impacts are indeed more intense, with a stronger decrease in discharge, a higher increase in actual evapotranspiration, and an additional decrease in the level of the water table, at least in the case of the observation wells under the irrigated zone. Observation wells which are away from the intensely irrigated fields, such as Po8, exhibit a more complicated behavior. However, if the catchment is not irrigated, certain hydrological impacts are less intense. For example, discharge and the distance to the water table decrease less during droughts in future climate than in present one. A possible explanation for this behavior is linked to evaporation. In the non-irrigated case, the increase in ET_0 during droughts is not transferred to an increase in actual evapotranspiration because of the dry average conditions. Consequently, the higher ET_0 during drought in future climate has a low impact on the hydrology. Hence, impacts of climate change are lower under very dry conditions. This is probably also why drought indices which include ET_0 are better at predicting discharge when irrigation is present, while the quality of their prediction is lower when the catchment is not irrigated: The presence of irrigation increases water availability, which increases the importance of ET_0 on the hydrological impacts of droughts, notably a decrease in discharge.

5 Discussion

Outputs from global or regional climate models are often used to predict changes of droughts in future climates because these outputs are easy to obtain and relatively simple to analyze. In most cases, the analysis is based on the computation of meteorological drought indices. To use drought indices in climate-impact studies, it is necessary to choose a particular set of indices. Based on the assessment of correlation coefficients and stability of the relationships between hydrological variables and drought indices, the drought indices RDI, RAI, and SPEI are the most suitable indices in our case study. However, their performance strongly depends on the assumed irrigation scenarios and may thus be different in other climates and land-uses. Other drought indices might perform better in more humid or colder climates. However, based on this study, these three indices are the most suitable for climate-impact studies in Mediterranean climate.

On a broader level, we propose to use drought indices with a certain caution in climate-impact studies and advise against using a single drought index. A hydrological model is a more direct way to analyze hydrological drought impacts in future climate and it should be used whenever possible in such studies. Unfortunately, the development and the parameter calibration of hydrological models is a complicated task and depends on the availability of hydrological measurements such as discharge and hydraulic heads.

If the development of a hydrological model is not an option, our results suggest that outputs from drought indices should be analyzed in detail with respect to three issues, regardless of the set of the chosen drought indices:

1. The importance of potential evapotranspiration (ET_0): Many meteorological drought indices only consider precipitation. Because these indices neglect the predicted increase in ET_0, their uses could lead to an underestimation of future drought risks. This has been reported in previous studies, notably by Dubrovsky et al. (2009) and Zarch et al. (2015). Our study confirms that drought indices which neglect ET_0 predict smaller changes in droughts than those which include ET_0 (Sect. 4.3). However, we found that some indices that include ET_0, such as SPEI, predict larger changes in drought severity compared to the simulations with the hydrological model (Sect 4.2), especially in scenarios with low soil moisture (scenario NOIRR). This was not previously considered and it indicates that, under some circumstances, the influence of ET_0 can be overestimated. In our case study, the influence of ET_0 is higher in the irrigated scenarios (PIRR/FUTIRR) with a high water availability. Hence, we can speculate that using drought indices which include ET_0 is more important in wetter climates, such as the ones in northern Europe, than in the Mediterranean climate. However, this hypothesis should be tested further in real case studies.

2. Correlation coefficients are not always sufficient to compare drought indices: Our comparison of the correlation coefficients between hydrological variables and drought indices (Sect 4.1) leads to similar results than previous studies. For example, Vicente-Serrano et al. (2012) compared the correlation between standardized stream flow (SSI) at monthly time scale and 6 drought indices, including SPI, SPEI, PDSI, and PHDI. SPEI showed the best correlation with discharge - results that we could reproduce (Fig. 5). SPI has a lower correlation than SPEI, but the difference is relatively small in both studies. However, more detailed investigations of the relationships between the drought indices and hydrological variables provide new insights which are not possible to obtain by using correlation coefficients alone. For instance, the correlation coefficients between drought indices and annual mean discharge are similar in all scenarios and all climates within our study, while the regression coefficients change in future climate, and they do so differently in different irrigation scenarios. Hence, impacts of irrigation and climate on drought indices are better understood if we use analysis tools beyond correlation coefficients.

3. The hydrological impacts of droughts depend on climate change: This has been previously explored in other studies, notably in studies focusing on hydrological droughts. For instance, Wanders et al. (2015) proposed a method to adapt the low-flow threshold defining the start of a hydrological drought as a function of the advance of climate change. The goal was to account for changes in the responses of low flows to droughts in a changing climate. However, these changes are also important when studying meteorological droughts. In this field, it is often assumed that the same lack of precipitation would have the same (hydrological) effects in present and future climate. However, this is not always the case (Sect 4.2). Investigating changes in frequency and intensity of meteorological droughts results in biased predictions of climate change impacts if changes in the hydrological processes are not considered.

6 Conclusions

The interpretation of changes in meteorological drought indices between future and present climates can be considerably compromised by the assumption that the relationship between the drought indices and the hydrological variables (which represent the effects of drought) is identical in present and future climate. The same drought-index value might lead to different drought consequences in present and future climate. Results can be further compromised by neglecting the increase in ET_0. In our case study, drought indices that take into account precipitation only (SPI, RAI, and EDI) underestimate the impact of droughts on water deficit and discharge often. By contrast, indices which give a high weight to ET_0 (as SPEI) sometimes overestimate the impact of future droughts on discharge, especially in the absence of irrigation.

As a summary, in the Lerma catchment, drought indices are useful indicators of dry periods in all tested climates and land-uses. However, a change in a particular drought index in future climate cannot easily be transferred to hydrological effects of droughts. In a stationary climate, the relationships between drought impacts and drought indices are usually reliable and so the hydrological consequences of droughts can be assessed from the drought indices. However, these relationships may change in a non-stationary climate and their evolution strongly depends on the particular combination of drought index and land-use. Hence, projections of future droughts using only one drought index may results in misleading estimation of the possible drought impacts.

Because drought indices can be estimated directly from the outputs of climate models, they are popular metrics of droughts even though they cannot be related uniquely to hydrological or even ecological impacts of droughts. Rather than relying on these indices, we recommend using a hydrological model to study hydrological effects of future droughts whenever possible. If setting up a hydrological model is not feasible, we advise to consider more than a single drought index and choose drought indices that take both precipitation and ET_0 into account. We also advise to test the chosen drought indices against measured or modeled results.

Regardless of the chosen drought index or of the climate scenarios, this study, and many previous studies (e.g., Blenkinsop and Fowler, 2007), predict an increase in the severity of droughts in the next fifty years in northern Spain. Adaptation to the new climatic conditions will therefore be necessary. The complexity of hydrological predictions should not prevent a timely adjustment of the urban water and irrigation networks. In northern Spain, a particular attention should be given to the future management of irrigation water because of the large dependency of local agriculture on irrigation.

7 Data availability

Hydrological data from the Lerma catchment have been collected and is owned by the Spanish Geological Survey (e.g., Merchán et al., 2013). Meteorological data have been collected by the Spanish meteorological national agency (AEMET) and is currently proprietary. Data from the ENSEMBLES project are available at: http://ensemblesrt3.dmi.dk/.

Acknowledgements. We show our appreciation to H. Fowler and S. Blenkinsop for providing the weather generators and for their support. Moreover, we thank the Spanish meteorological national agency (AEMET) to provide us the meteorological data. In addition, we acknowledge the ENSEMBLES project, funded by the European Commission's 6th Framework Programme (contract number: GOCE-CT-2003-505539), to provide us the outputs from the regional climate models. Research in the Lerma catchment is supported by the Spanish Ministry of Economy and Competitiveness within the framework of project AgroSOS (FEDER funds [EU], grant CGL2015-66016-R). The publication of this article is supported by the Deutsche Forschungsgemeinschaft and the "open access publishing fund" of the University of Tübingen. This study was performed within the International Research Training Group "Integrated Hydrosystem Modeling" (grant GRK 1829/1 of the Deutsche Forschungsgemeinschaft).

References

Abrahao, R., Causapé, J., García-Garizábal, I., and Merchán, D.: Implementing irrigation: Water balances and irrigation quality in the Lerma basin (Spain), Agricult. Water Manag., 102, 97–104, 2011.

Agwata, J.: A review of some indices used for drought studies, Civil and Environmental research, 6, 14–21, 2014.

Allen, R., Pereira, L., Raes, D., and Smith, M.: Crop evapotranspiration (guidelines for computing crop water requirements), FAO irrigation and drainage paper, 56, 2000.

Bachmair, S., Kohn, I., and Stahl, K.: Exploring the link between drought indicators and impacts, Nat. Hazard and Earth Sys., 15, 1381–1397, 2015.

Beltrán, A.: Estudio de los suelos de la zona regable de Bardenas II. Sectores VIII, IX, X, XII y XIII., Instituto Nacional de Reforma y Desarrollo Agrario, Ministerio de Agricultura, Pesca y Alimentación, 1986.

Blenkinsop, S. and Fowler, H.: Changes in European drought characteristics projected by the PRUDENCE regional climate models, Int. J. Climatol., 27, 1595 – 1610, 2007.

Bloomfield, J. and Marchant, B.: Analysis of groundwater drought building on the standardised precipitation index approach, Hydrol. Earth Syst. Sci., 17, 4769–4787, 2013.

Bovolo, C., Blenkinsop, S., Majone, B., Zambrano-Bigiarini, M., Fowler, H., Bellin, A., Burton, A., Barceló, D., Grathwohl, P., and Barth, J.: Climate change, water resources and pollution in the Ebro basin: towards an integrated approach, in: The Ebro River Basin, edited by Barceló, D. and Petrovic, M., Springer-Verlag, 2010.

Burke, E. J., Brown, S. J., and Christidis, N.: Modeling the recent evolution of global drought and projections for the twenty-first century with the Hadley Centre climate model, J. Hydrometeor., 7, 1113–1125, 2006.

Burton, A., Kilsby, C., Fowler, H., Cowpertwait, P. S. P., and O'Conell, P.: RainSim: A spatial-temporal stochastic rainfall modelling system, Environ. Mod. Software, 23, 1356–1369, 2008.

Burton, A., Fowler, H., Blenkinsop, S., and Kilsby, C.: Downscaling transient climate change using a Neyman-Scott Rectangular Pulses stochastic rainfall model, J. Hydrol., 381, 18–32, 2010.

Byun, H.-R. and Wilhite, D.: Objective quantification of drought severity and duration, J. Climate, 12, 2747–2756, 1999.

Collins, M., Booth, B., Harris, G., Murphy, J., Sexton, D., and Webb, M.: Towards quantifying uncertainty in transient climate change, Clim. Dyn., 27, 127–147, 2006.

Dai, A.: Drought under global warming: a review, Wiley Interdisciplinary Reviews: Climate Change, 2, 45–65, 2011.

Dubrovsky, M., Svoboda, M., Trnka, M., Hayes, M., Wilhite, D., Zalud, Z., and Hlavinka, P.: Application of relative drought indices in assessing climate-change impacts on drought conditions in Czechia, Theor. Appl. Climatology, 96, 155–171, 2009.

Flato, G. J. M., Abiodun, B., Braconnot, P., Chou, S., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., C.Forest, Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., and Rummukainen, M.: Evaluation of climate models, in: The physical science basis. Contribution of working group I to the fifth assessment report of the Intergovernmental Panel on Climate Change, edited by Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K., Tignor, M., and Miller, H., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2013.

Gil, M., Garrido, A., and Gómez-Ramos, A.: Economic analysis of drought risk: An application for irrigated agriculture in Spain, Agr. Water Manage., 98, 823–833, 2011.

Graveline, N., Majone, B., Duiden, R. V., and Ansink, E.: Hydro-economic modeling of water scarcity under global change: an application to the Gallego river basin (Spain), Reg. Environ. Change, 14, 119–132, 2014.

Hayes, M. and Lowrey, J.: Drought indices, Intermountain West Climate Summary, pp. 1–6, 2007.

Hazewinkel, M.: Encyclopedia of mathematics, Springer (Kluwer Academic Publishers), 2001.

Heim, R.: A review of the twentieth-century drought indices used in the United States, B. Am. Meteorol. Soc., 83, 1149–1165, 2002.

Herrera, S., Fita, L., Fernández, J., and Gutiérrez, J. M.: Evaluation of the mean and extreme precipitation regimes from the ENSEMBLES regional climate multimodel simulations over Spain, J. Geophys. Res., 115, D21 117, 2010.

Hisdal, H., Stahl, K., Tallaksen, L., and Demuth, S.: Have streamflow droughts in Europe become more severe or frequent?, Int. J. Climatol., 21, 317–333, 2001.

Holman, I., Tascone, D., and Hess, T.: A comparison of stochastic and deterministic downscaling methods for modelling potential groundwater recharge under climate change in East Anglia, UK: implications for groundwater resource management, Hydrogeol. J., 17, 1629–1641, 2009.

Jacob, D., Van den Hurk, B., Andrae, U., Elgered, G., Fortelius, C., Graham, L. P., Jackson, S. D., Karstens, U., Köpken, C., Lindau, R., Podzun, R., Rockel, B., Rubel, F., Sass, B. H., Smith, R. N. B., and Yang, X.: A comprehensive model inter-comparison study investigating the water budget during the BALTEX-PIDCAP period, Meteorol. Atmos. Phys., 77, 19–43, 2001.

Jaeger, E., Anders, I., Lüthi, D., Rockel, B., Schär, C., and Seneviratne, S.: Analysis of ERA40-driven CLM simulations for Europe, Meteorol. Zeitung, 17, 349–367, 2008.

Keyantash, J. and Dracup, J. A.: The quantification of drought: An evaluation of drought indices, B. Am. Meteorol. Soc., 83, 1167–1180, 2002.

Kilsby, C., Jones, P., Burton, A., Ford, A., Fowler, H., Harpham, C., James, P., Smith, A., and Wilby, R.: A daily weather generator for use in climate change studies, Environ. Mod. Software, 22, 1705 – 1719, 2007.

Kim, B. S., Park, I. H., and Ha, S. R.: Future projection of droughts over South Korea using representative concentration pathways (RCPs), Terr. Atmos. Ocean Sci., 25, 673–688, 2014.

Kirono, D., Kent, D., Hennessy, K., and Mpelasoka, F.: Characteristics of Australian droughts under enhanced greenhouse conditions: Results from 14 global climate models, J. Arid Environ., 75, 566–575, 2011.

Kumar, R., Musuuza, J. L., van Loon, A. F., Teuling, A. J., Barthel, R., Broek, J., Mai, J., Samaniego, L., and Attinger, S.: Multiscale evaluation of the standardized precipitation index as a groundwater drought indicator, Hydrol. Earth Syst. Sci., 20, 1117–1131, 2016.

Leng, G., Tang, Q., and Rayburg, S.: Climate change impacts on meteorological, agricultural and hydrological droughts in China, Global Planet. Change, 126, 23–34, 2015.

Li, H., Sheffield, J., and Wood, E.: Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching, J. Geophys. Res., 115, D10 101, 2009.

Majone, B., Bovolo, C., Bellin, A., Blenkinsop, S., and Fowler, H.: Modeling the impacts of future climate change on water resources for the Gallego river basin (Spain), Water Resour. Res., 48, W01 512, 2012.

Masud, M., Khaliq, M., and Wheater, H.: Analysis of meteorological droughts for the Saskatchewan River Basin using univariate and bivariate approaches, J. Hydrol., 522, 452 – 466, 2015.

Mavromatis, T.: Drought index evaluation for assessing future wheat production in Greece, Int. J. Climatol., 27, 911–924, 2007.

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, Eighth Conference on Applied Climatology, Anaheim, California,, 1, 179–184, 1993.

Meehl, G., Stocker, T., Collins, W., Friedlingstein, P., Gaye, A., Gregory, J., Kitoh, A., Knutti, R., Murphy, J., Noda, A., Raper, S., Watterson, I., Weaver, A., and Zhao, Z.: Global climate projections, in: The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change, edited by Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K., Tignor, M., and Miller, H., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2007.

Merchán, D., Causapé, J., and Abrahao, R.: Impact of irrigation implementation on hydrology and water quality in a small agricultural bassin in Spain, Hydrolog. Sci. J., 58, 1400–1413, 2013.

Mishra, A. and Singh, V.: A review of drought concepts, J.Hydrol., 391, 202–216, 2010.

Nakićenović, N., Davidson, O., Davis, G., Grübler, A., Kram, T., Rovere, E. L. L., Metz, B., Morita, T., Pepper, W., Pitcher, H., Sankovski, A., Shukla, P., Swart, R., Watson, R., and Dadi, Z.: Emission scenarios - Summary for policymakers, Intergovernemental Panel on Climate Change - Special Report, 2000.

Nash, J. and Sutcliffe, V.: River flow forecasting through conceptual models, part I- A discussion of principles, J. Hydrol., 10, 282–290, 1970.

Niemeyer, S.: New drought indices, Options Méditerranéenes, Séries A:, 80, 267–274, 2008.

Palmer, W.: Meteorological drought, Office of Climatology, U.S. Departement of commerce, 45, 1–58, 1965.

Park, C.-K., Byun, H.-R., Deo, R., and Lee, B.-R.: Drought prediction till 2100 under RCP 8.5 climate change scenarios for Korea, J. Hydrol., 526, 221–230, 2015.

Plata-Torres, J.: Informe sobre la campaña de sondeos eléctrico verticales efectuados en el barranco de Lerma (Zaragoza), Grupo de Geofísica del Instituto Geológico y Minero de España, 2012.

Prudhomme, C., Reynard, N., and Crooks, S.: Downscaling of global climate models for flood frequency analysis: Where are we now?, Hydrol. Processes, 16, 1137–1150, 2002.

Quiring, S. and Papakryiakou, T. N.: An evaluation of agricultural drought indices for the Canadian prairies, Agr. Forest Meteorol., 118, 49–62, 2003.

Samaniego, L., Kumar, R., and Zink, M.: Implications of parameter uncertainty on soil moisture drought analysis in Germany, J. Hydrometeorol., 14, 47–68, 2013.

Sánchez, E., Gallardo, C., Gaertner, M., Arribas, A., and Castro, M.: Future climate extreme events in the Mediterranean simulated by a regional climate model: A first approach, Global Planet. Change, 44, 163–180, 2004.

Srikanthan, R. and McMahon, T.: Stochastic generation of annual, monthly and daily climate data: A review, Hydrol. Earth Sys. Sci., 5, 653–670, 2001.

Stahl, K., Kohn, I., Blauhut, V., Urquijo, J., de Stefano, L., Acacio, V., Dias, S., Stagge, J., Tallaksen, L. M., Kampragou, E., van Loon, A., Barker, L., Melsen, L., Bifulco, C., Musolino, D., de Carli, A., Massarutto, A., Assimacopoulos, D., and van Lanen, H.: Impacts of European drought events: insights from an international database of text-based reports, Nat. Hazards Earth Syst. Sci. Discuss., 3, 5453–5492, 2015.

Svoboda, M., Hayes, M., and Wood, D.: Standardized precipitation index user guide, World Meteorological Organization, 1090, 1–24, 2012.

Szép, I., Mika, J., and Dunkel, Z.: Palmer drought severity index as soil moisture indicator: physical interpretation, statistical behaviour and relation to global climate, Phys. Chem. Earth, 30, 231–245, 2005.

Therrien, R.: HydroGeoSphere - A three-dimensional numerical model describing fully-integrated subsurface and surface flow and solute transport., Ph.D. thesis, Université Laval and University of Waterloo, 2006.

Therrien, R., McLaren, R., Sudicky, E., and Panday, S.: HydroGeoSphere: A three-dimensional numerical model describing fully-integrated subsurface and surface flow and solute transport - user manual, University of Waterloo, 2010.

Toews, M. and Allen, D.: Evaluating different GCMs for predicting spatial recharge in an irrigated arid region, J. Hydrol., 374, 265–281, 2009.

Tsakiris, G. and Vangelis, H.: Establishing a drought index incorporating evapotranspiration, European Water, 9, 3–11, 2005.

Tue, V. M., Raghavan, S. V., Minh, P., and Shie-Yui, L.: Investigating drought over the Central Highland, Vietnam, using regional climate models, J. Hydrol., 526, 265–273, 2015.

van der Linden, P. and Mitchell, J.: ENSEMBLES: Climate change and its impact: Summary of research and results from the ENSEMBLES project, Met Office Hadley Centre, UK, 1, 1–160, 2009.

van Genuchten, M.: A closed-form equation for predicting the hydraulic conductivity of unsaturated soils, Soil. Sci. Soc. Am. J., 44, 892–898, 1980.

Vicente-Serrano, S., Beguería, S., and López-Moreno, J. I.: A Multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index, J. Climate, 23, 1696–1718, 2009.

Vicente-Serrano, S. M., Beguería, S., Lorenzo-Lacruz, J., Camarero, J., López-Moreno, J., Azorin-Molina, C., Revuelto, J., Morán-Tejeda, E., and Sanchez-Lorenzo, A.: Performance of drought indices for ecological, agricultural, and hydrological applications, Earth Interact., 16, 1–27, 2012.

Vicente-Serrano, S. M., van der Schrier, G., Beguería, S., Azorin-Molina, C., and López-Moreno, J. I.: Contribution of precipitation and reference evapotranspiration to drought indices under different climates, J. Hydrol., 526, 42–54, 2015.

von Gunten, D., Wöhling, T., Haslauer, C., Merchán, D., Causapé, J., and Cirpka, O.: Efficient calibration of a distributed *pde*-based hydrological model using grid coarsening, J. Hydrol., 519, 3290–3304, 2014.

von Gunten, D., Wöhling, T., Haslauer, C., Merchán, D., Causapé, J., and Cirpka, O.: Estimating climate-change effects on a Mediterranean catchment under various irrigation conditions, J. Hydrol. Reg. Stud., 4, 550–570, 2015.

Wanders, N., Wada, Y., and van Lanen, H.: Global hydrological droughts in the 21st century under a changing hydrological regime, Earth Syst. Dynam., 6, 1–15, 2015.

Wilhite, D. A. and Glantz, M. H.: Understanding the drought phenomenon: The role of definitions, in: Planning for drought: Toward a reduction of societal vulnerability, edited by Wilhite, D. A., Easterling, W. E., and Wood, D. A., pp. 11–27, Westview Press, 1985.

Zarch, M. A. A., Sivakumar, B., and Sharma, A.: Droughts in a warming climate: A global assessment of standardized precipitation index (SPI) and reconnaissance drought index (RDI), J. Hydrol., 526, 183 –195, 2015.

Zargar, A., Sadiq, R., Naser, B., and Khan, F. I.: A review of drought indices, Environ. Rev., 19, 333–349, 2011.

Table 1. A summary of the drought indices used in this study.

Indices	Acro-nym	Input	Chosen time scale	Reference
Standardized precipitation index	SPI	P	12 months	Svoboda et al. (2012)
Standardized precip. evapo. index	SPEI	P, ET_0	12 months	Vicente-Serrano et al. (2009)
Rainfall anomaly index	RAI	P	12 months	Keyantash and Dracup (2002)
Effective drought index	EDI	P	12 months	Byun and Wilhite (1999)
Palmer drought severity index	PDSI	P, ET_0	$\sim$ 9 months	Palmer (1965)
Palmer hydrological drought index	PHDI	P, ET_0	$\sim$ 9 months	Palmer (1965)
Reconnaissance drought index	RDI	P, ET_0	12 months	Tsakiris and Vangelis (2005)

Table 2. Name and acronym of the regional climate models used in this study. - Adapted from Herrera et al. (2010) and von Gunten et al. (2015).

Acronym	RCM	GCM	Reference
ETHZ	CLM	HadCM3	Jaeger et al. (2008)
METO	HadRM3	HadCM3	Collins et al. (2006)
MPI	M- REMO	ECHAM5	Jacob et al. (2001)
UCLM	PROMES	HadCM3	Sánchez et al. (2004)

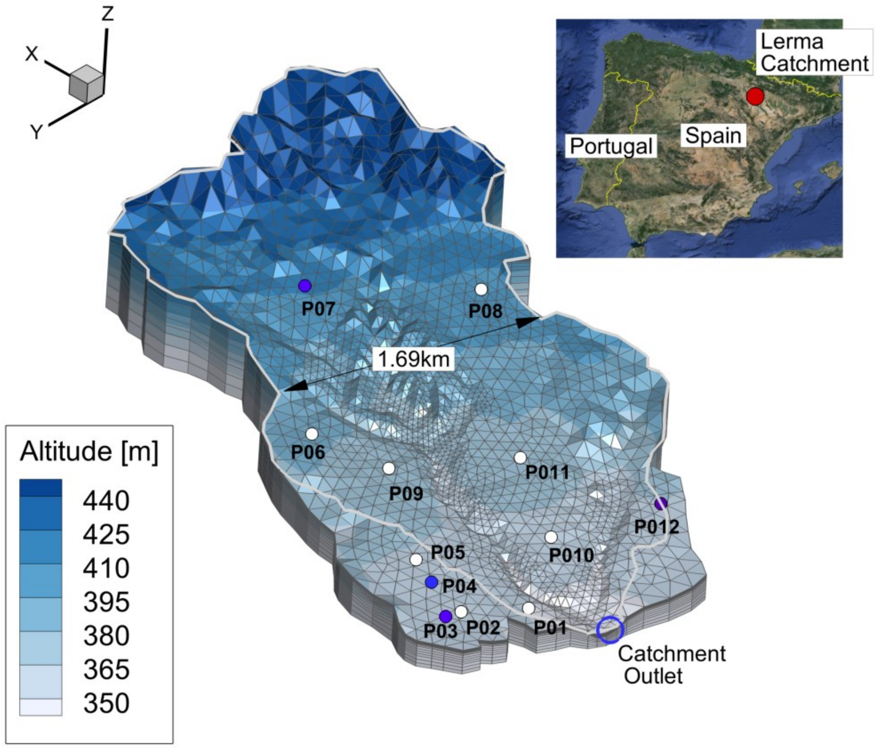

Figure 1. Surface elevation of the Lerma catchment (masl.). The observation wells drilled in 2010 are indicated by blue circles and the ones drilled in 2008 are indicated by white circles. The gray line represents the limits of the surface flow domain. Vertical exaggeration: 5:1. Modified from von Gunten et al. (2014, 2015).

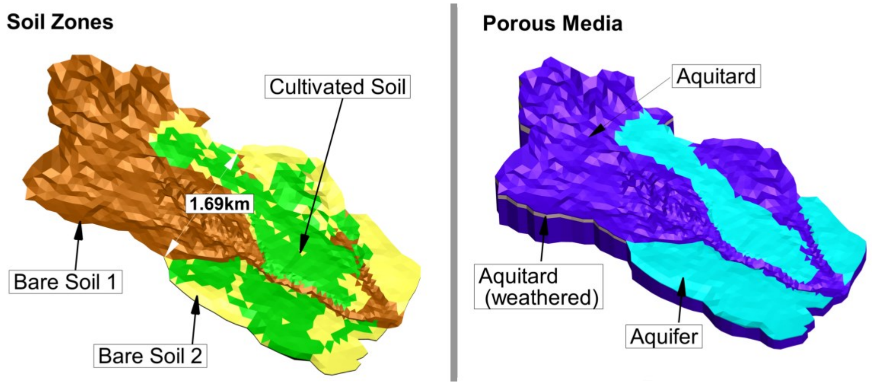

Figure 2. Soil and hydrogeological zones for the year 2009. Vertical exaggeration: 5:1. Modified from von Gunten et al. (2014, 2015).

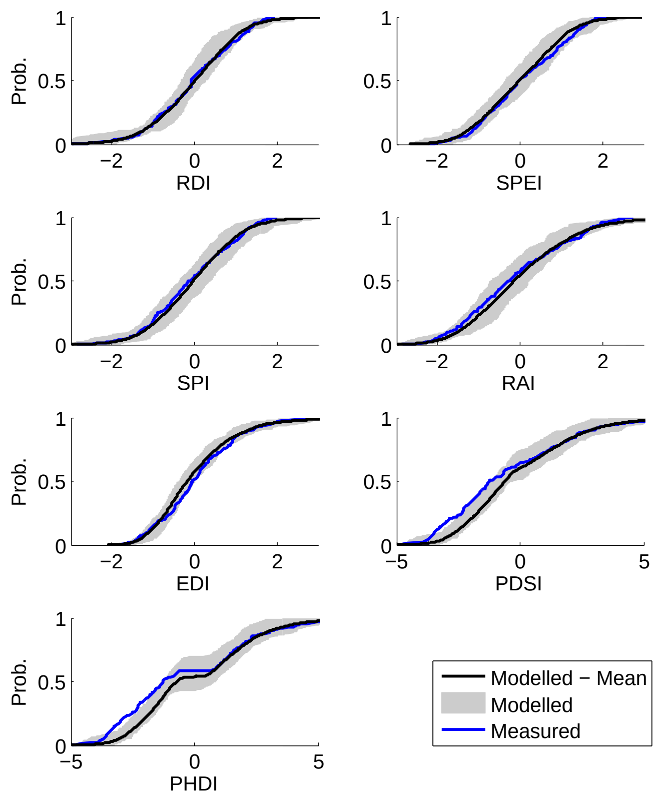

Figure 3. Empirical cumulative distribution function (*ecdf*) of drought indices based on measurement time series (in blue) and based on the outputs from the weather generator (in black). The gray area represents the boundaries of the 15 *ecdf* of drought indices based on the outputs from the weather generator when these outputs are cut at the same length that the measurement time series (23 years).

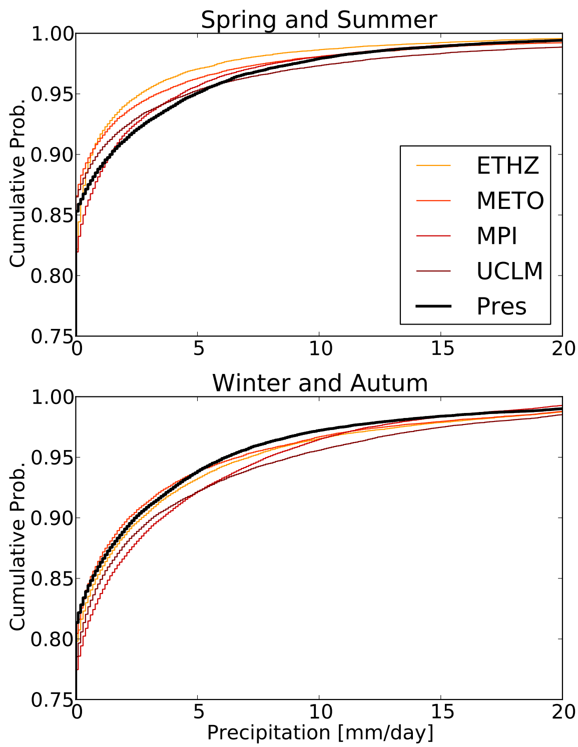

Figure 4. Empirical cumulative distribution functions of daily precipitation for present and future climate scenarios.

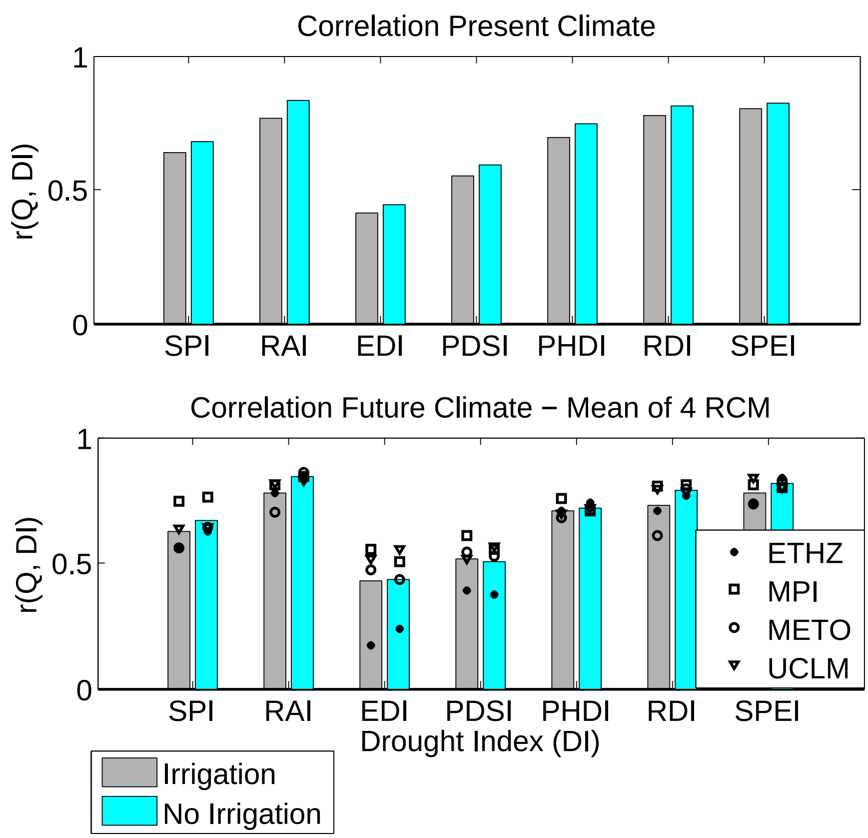

Figure 5. Correlation coefficient r between the drought indices and discharge. The irrigation scenarios are PIRR in the present climate and FUTIRR in the future climate. In future climate (bottom panel), the plotted bars are the average of the outputs of the four regional climate models. See Table 2 for information about the four regional climate models.

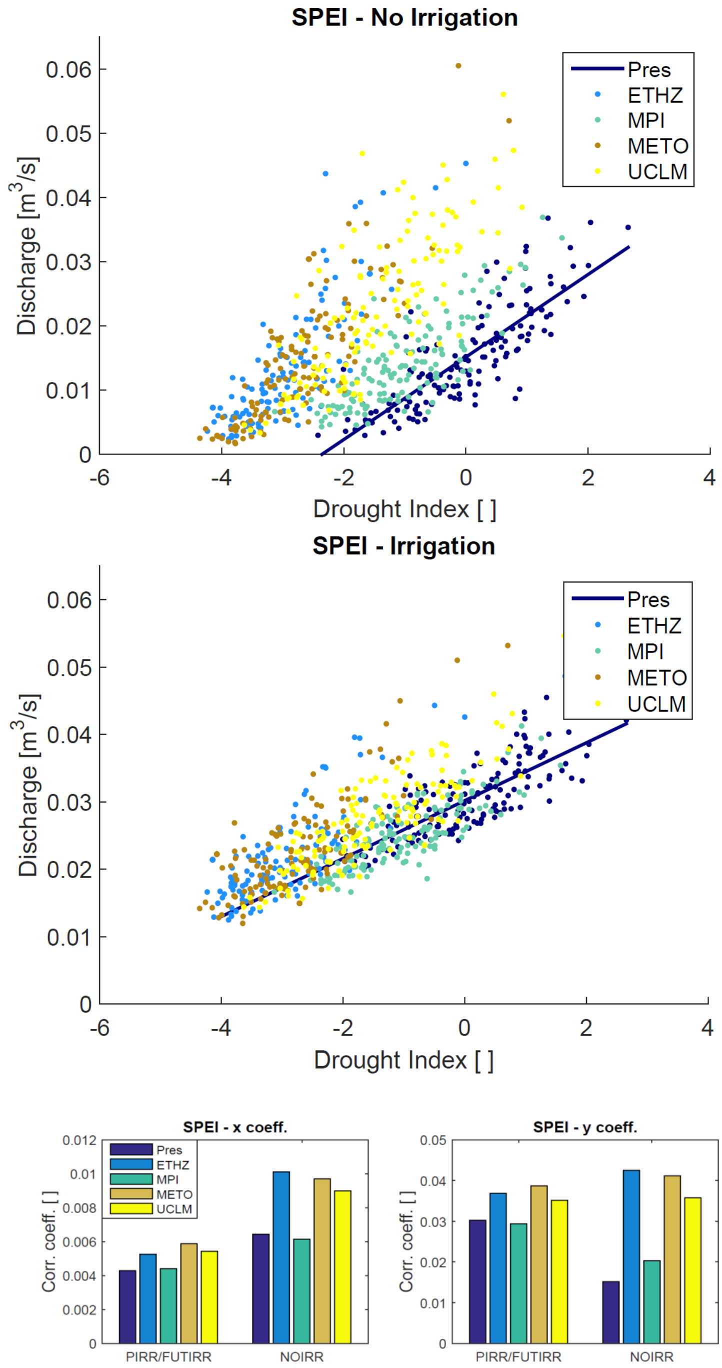

Figure 6. Performance of SPEI in future climate for annual discharge. The blue line is the linear regression between SPEI and discharge in present climate. Top panel: NOIRR scenario, large model bias. Second panel: FUTIRR scenario, no significant model bias. Bottom panel: the two coefficients of the linear regression between Q and SPEI in each climate.

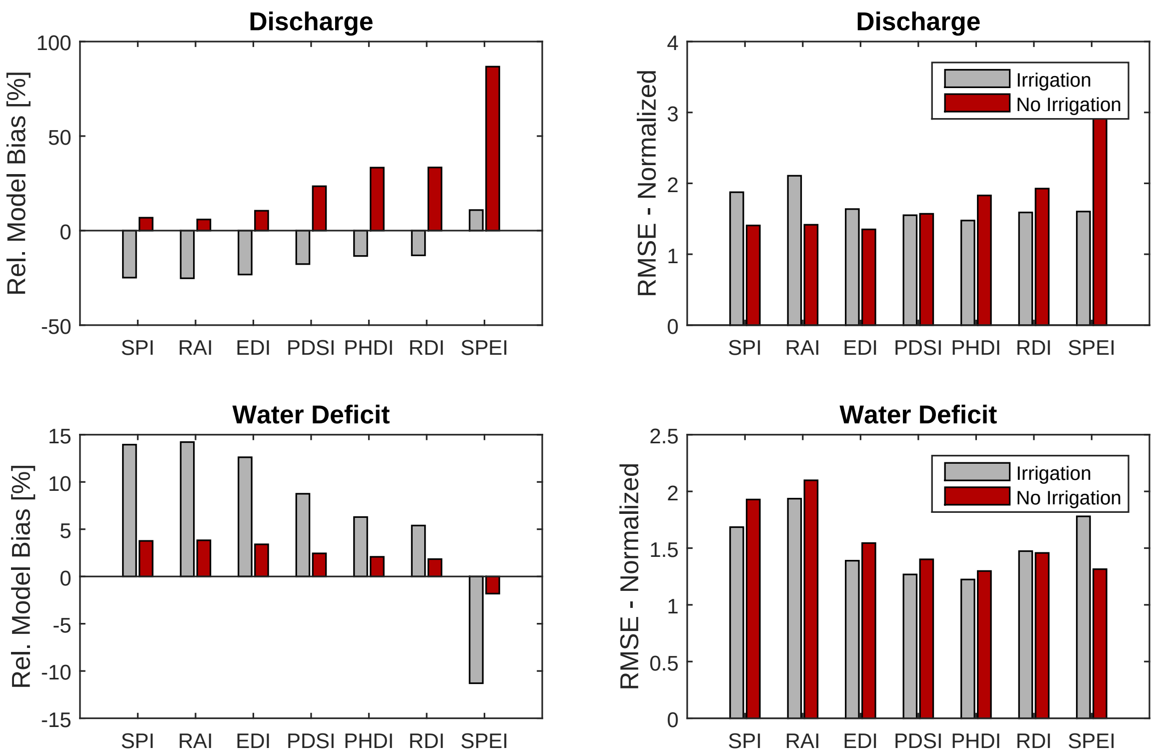

Figure 7. Relative model bias and NRMSE in the NOIRR and PIRR/FUTIRR irrigation scenarios. The results are based on the average of the outputs of the four regional climate models (Table 2).

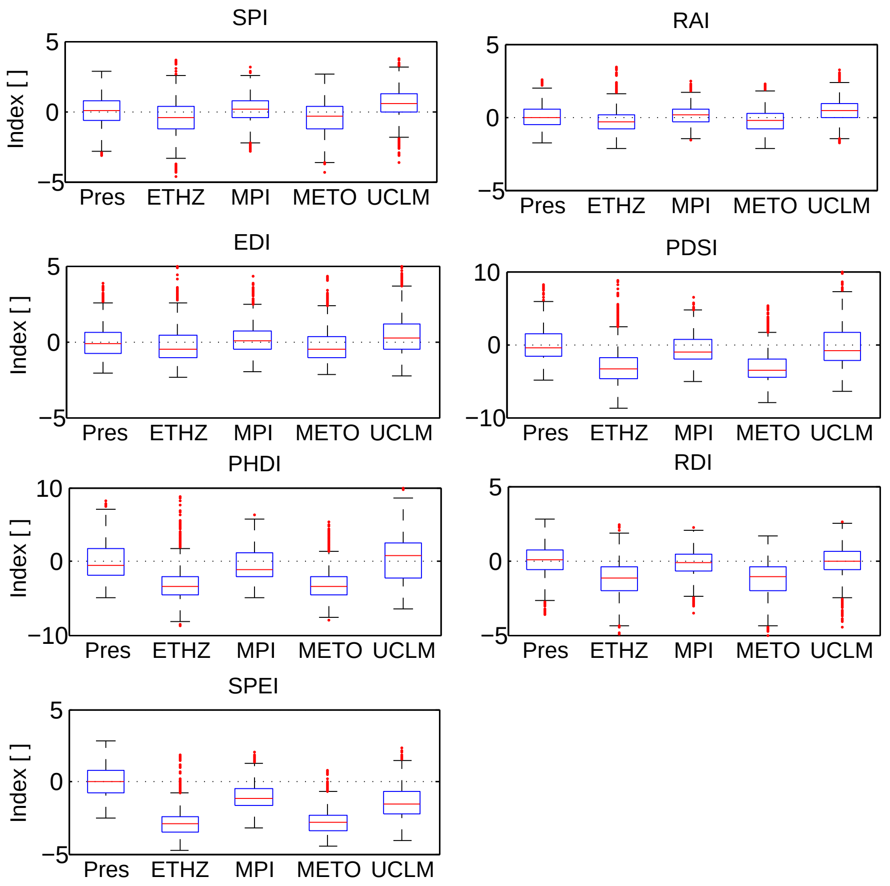

Figure 8. Present and future (2040-2050) droughts predicted by the seven drought indices, using the outputs from the weather generator. See Table 2 for information about the four regional climate models.

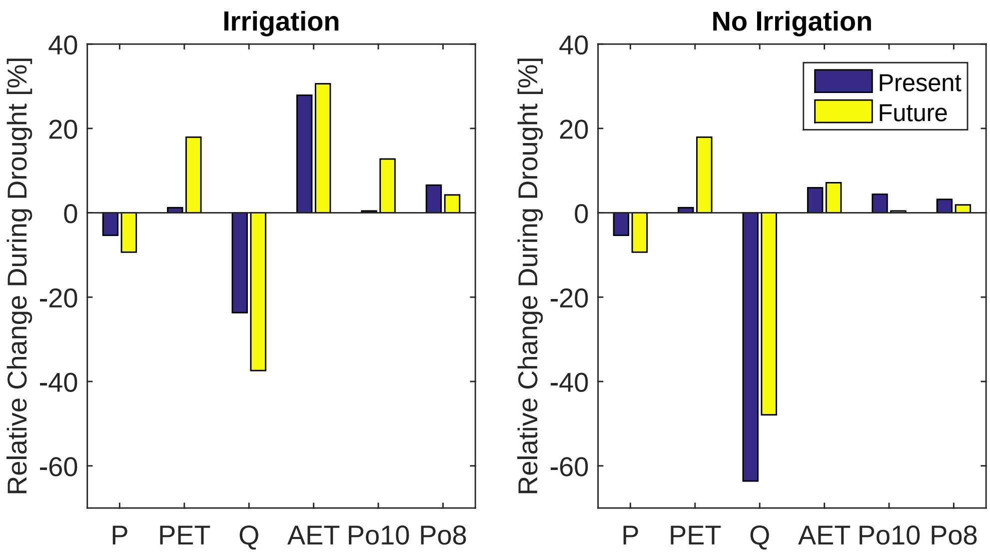

Figure 9. Average hydrological impacts of present and future (2040-2050) droughts. From left to right: Relative changes in mean annual precipitation, ET_0, discharge, actual evapotranspiration, and water-table depth at the observation wells Po8 and Po10. For simplicity, droughts are here defined as years with a SPEI- and a SPI-value lower than one. Future conditions are based on the average of the outputs of the four regional climate models (Table 2).