NOTE: This document includes (1) a **summary of the most relevant revisions** made in the manuscript, (2) a **point-by-point response** to the reviewer's comments, (2), as well as (3) the **revised manuscript**. Changes in the manuscript were made using "track changes", so that these can be identified easily. Page and line numbers in the point-by-point response refer to the final revised manuscript (clean version without track changes).

Most relevant changes made in the manuscript

- Key terms that build the basis for our analysis (i.e. exposure, vulnerability, hazard) are now clearly defined in the revised manuscript (building on latest IPCC definitions). Vulnerability and hazard were already defined in the initial version; we have now added a clear definition of exposure.
- The hazard/exposure analysis for rainfed systems was computed at grid-cell level (now the results for both systems, rainfed and irrigated, are available at grid-cell level)
- A table was added that provides an overview of the hazard and exposure indicators used in the analysis and their processed input data (Table 1)
- The drought risk assessment for both rainfed and irrigated agricultural systems was computed again with the new grid-cell data (for rainfed systems). Tables and figures related to it where changed accordingly
- The discussion was revised, further emphasizing opportunities, limitations, and potential future research needs
- A more in-depth comparison of our results and the results of the global risk assessment by Carrao et al. (2016) was added to the discussion chapter

Point-by-point response to reviewer's comments

Referee #1 (Anonymous)

The authors present a relevant and interesting manuscript, where they have studied and mapped composite drought risk at the global scale. For assessing agricultural drought risk, they have separated drought hazard/exposure in irrigated and rainfed cropping systems, and combined these hazard indicators with socio-ecological vulnerability. Finally, they have compared the obtained drought risk metric, with reported drought hazard events from EM-Dat. In general, I like and agree with the approach described in the study. My notes about the study are written below.
Many thanks for the overall positive feedback.

1. I very much agree with looking into drought hazard for irrigated and rainfed cropping systems separately. However, the way these hazard indicators are combined, is potentially misleading. The hazard indicators are combined in a way that equalizes the weight of drought hazards in irrigated and rainfed cropping systems. However, as irrigated systems are, in general, more resilient to drought (irrigated systems can mitigate drought impacts by irrigation while rainfed systems cannot), equalizing the hazard associated with rainfed and irrigated systems, does not seem sensible. Further, if I understand correctly, based on the analyses, drought is more frequent in irrigated cropping systems compared to rainfed systems, which is not something that would be initially expected (Page 7, Lines 193-194). To make the methods comparable across rainfed and irrigated cropping systems, the authors could potentially define droughts for rainfed systems as for irrigated systems, but without the option to compensate the demand deficit by irrigation.
We agree that combining the indicators for rainfed and irrigated drought risk may be misleading, and we have highlighted this aspect already in the discussion section (**lines 434-437**). However, we don't agree that irrigated systems are in general more resilient than rainfed systems. The way how rainfed and irrigated systems mitigate drought is different. In rainfed systems crops are often cultivated in the wet season and soil conservation methods or water concentration are used to accumulate soil moisture in the cropped soils. Irrigated systems allow crop cultivation in arid regions or in the dry period of the year. For example, half of the global irrigated

land is located in arid and semi-arid regions (Siebert et al., 2015) and the majority of irrigation water requirement in South Asia is in the dry Rabi season (Biemans et al., 2016). However, these systems rely heavily on the functioning of the water supply infrastructure, which is often extremely complex. There are many reasons why water supply to irrigated fields often fails in practise, in particular during drought events. We account for these differences by using different indicators to calculate drought hazard for rainfed and irrigated systems.

We agree that our assumption of a similar weight for irrigated and rainfed hazard is questionable, but to quantify these weights would require a lot of region specific information that is not available at global scale (we mention this aspect in the discussion).

We want to highlight that the reasoning for the calculation of the total risk in this manuscript was less to support comparisons across countries but to account for the different extend of irrigated and rainfed systems within the specific countries. There are countries in which crop production is completely rainfed and countries in which all crops are irrigated so that only the risk for the rainfed or irrigated systems are relevant. Except from these extremes, crop production in most countries is either predominantly irrigated or predominantly rainfed. We account for this by calculating total risk as the harvested area weighted mean of the rainfed versus irrigated drought risk. We added some lines to the revised version of the manuscript to explain this reasoning and to support the interpretation of the total risk maps **(P19, L437-443)**.

2. The vulnerability assessment includes a high number of indicators. Although, the authors have excluded variables that have >0.9 correlation, many of the indicators are still most likely highly correlated. Considering the method used for calculating the vulnerability metric, this would lead to some phenomena being unproportionally weighted in the composite vulnerability index. Further, with this many variables, it is also more difficult to pinpoint and isolate potential socio-economic entry-points for reducing drought vulnerability. Hence, it might be worthwhile to analyze how the variables correlate and identify the most relevant indicators using e.g. PCA.

Thanks for the comment. For the multicollinearity analysis we follow a standard approach for composite indicator construction, as e.g. described by OECD in their Handbook on Composite Indicator Construction (OECD, 2008). Indeed the multicollinearity analysis has revealed that several of the indicators are highly correlated with correlations >0.7. As mentioned in the methods section (lines **255-256**) we have decided to keep highly correlated indicators when they present different drivers of vulnerability (and hence different entry points for vulnerability reduction). We added some lines in the discussion **(P20, L464-466)**, where we mention this as a potential limitation of our work.

Regarding PCA, we understand that there are different approaches to identify a final set of weighted vulnerability indicators, incl. statistical approaches (e.g. PCA) and expert-based approaches. Here, an expert-based approach is applied where indicators were identified based on a review of the literature and their relevance was evaluated based on expert judgment (n = 78 experts participated in the weighting). We added a few lines in the discussion that statistical approaches (e.g. based on PCA) could have been an alternative to the expert-based approach used here, and indicate this as an outlook for future research to compare the findings of statistical and expert-based approaches (**P20, L471-476**). Such a comparison (PCA vs. expert-based approach) was conducted by Hagenlocher et al. (2013), who did not find significant impacts of the choice of the approach on the final vulnerability index.

3. Fig. 6: The comparison between the drought risk indicator developed here and the drought hazards observed in EM-DAT is a relevant and nice addition to the study. However, visually it does not seem that the amount of observed drought hazards correlate with the risk indicator presented. I would recommend showing a scatter plot about this relationship (especially, since the authors refer to this section as a validation of the proposed drought risk indicator), at least for those areas where data exist for both sources, so that the reader can assess their agreement more easily.

Thank you for the comment, a scatter plot will not improve the visualization of the results just because EM-DAT is not based on physical parameters to record droughts. The number in EM-DAT depends highly on data availability (some countries in Africa are frequently affected by drought, but this is not recorded consistently) and the size of a country is important (larger countries often indicate a higher number of drought events, e.g. China, USA, Russia). This is described in the manuscript (lines **402-408; 523-528**) and countries are mentioned as an example.

4. The authors have assessed the risk of drought by combining the associated hazard, exposure and vulnerability components. However, the difference between hazard and exposure is currently not clearly stated and defined in the manuscript. For example, what are the drought exposure and hazard components used for deriving the results in Figs 2 and 3. Further, it would be good to explicitly explain the exposure component in the text (exposure of what?), since also some of the vulnerability indicators could be viewed as being related to drought exposure (e.g. % of GDP from agriculture etc., rural population).
Thanks for the comment, following the IPCC (2014) definition of exposure as "elements located in areas that can be potentially affected by hazards", exposure in our analysis is directly related to the hazard. As described in section 2.1, we used rainfed and irrigated croplands according to the Monthly Irrigated and Rainfed Cropping Areas (MIRCA2000) dataset (Portmann et al., 2010) as the exposed element. We add the definition of exposure in the methods section (2.1 chapter, **P5, L115-116**). GDP from agriculture was included as a vulnerability indicator since countries with high dependency on agriculture, are more vulnerable to droughts; this indicator was also the most relevant indicator ranked by the experts.

5. The GCWM was forced with monthly data, which were transformed into pseudo daily climate. As products that readily have daily records exist (e.g. AgMerra, ISI-MIPforcing), why they chose to use monthly forcing data?
We agree that the way how pseudo-daily climate is generated from monthly input data represents a source of uncertainty. However, since drought is an event that develops slowly, we are confident that our basic findings are not affected by this limitation. For the methods how drought hazard is calculated in our study it does not matter much whether a rainfall event is a few days earlier or later.
We are aware of alternative data sets that could be used as climate input and in fact we started to process global reanalysis data to explore the potential of using these daily data in GCWM and WaterGAP as climate input. However, the products mentioned by the reviewer have own limitations. AgMerra is only available for the period until 2010, similar to some other climate data sets used by ISIMIP. Other data sets do not provide all the variables needed to calculate potential evapotranspiration using the Penman-Monteith method. WFD and some other products, for example, do not provide daily maximum and daily minimum temperatures which are essential to quantify accurately the vapor pressure deficit. Finally, ISIMIP input data have a resolution of 0.5 by 0.5 degree while GCWM is running on a native 5 arc minute resolution (0.0833 degree). Because of these challenges, we decided to use the well established CRU monthly climate input for the present paper and refer to future activities and future studies in which we will explore the use of daily climate input data.

6. Minor comment for structure: would be good to be consistent between methods and results in which order you present the results (method: rainfed, irrigated; results: irrigated, rainfed)
Thank you, we changed it accordingly.

7. It would be worthwhile to cross-refer to Fig. 1 in describing the methods, as it would make the methods easier to understand. This would also bind Fig. 1 better to the rest of text, as now it is a bit isolated from it.
Thank you for the comment, we changed it accordingly and add the fig. 01 through the text on lines **131, 139,177 and 280.**

8. I would recommend tabulating also the other data than vulnerability indicators used for the study, so that the reader can get an understanding of the data more quickly and easily.
Thanks for the suggestion. For a better understanding of which data was used for the hazard/exposure analysis we added an explanatory table **(Table 01)** with datasets and sources in section 2.1 **(P5, L125-127).**

9. Page 5 Rows 116-117: The definition of the MIRCA-areas is a bit unclear.
Thank you, we re-run the rainfed hazard/exposure assessment at pixel level, therefore it wasbe no need to describe the MIRCA-areas anymore, the text was revised to omit the lines that describe it (e.g. lines in the previous manuscript **116-118, 131-133, 136, 186, 190, 202-204**) and emphasis was placed on the analysis at pixel level.

10. Figures 2 and 3: The range for color scales of the figures should be the same, at least for the hazard and vulnerability figures. Currently, it is very difficult to assess the contribution of each component on the total risk factor, and it seems that the hazard component has a way stronger influence on the drought risk compared to vulnerability (the mapped patterns are essentially the same for hazard/exposure and risk).
We agree and are aware of this as a limitation from the values perspective, since the number depends on the set of variables and the methodology used. The different components have the same color scheme to better differentiate the minimum and maximum values of each one. However, the advantage of showing values is that

readers can reproduce why the risk map is colored like it is. We add how the classes were made in the caption of the figures to help the readers to make their own categorical classification while keeping the numerical info.

11. Why hazard/exposure for rainfed is computed at national/sub-national level? Further, why these are aggregated to national level in analyses of for agricultural systems? These aggregations make it hard to compare the different results. It is of course ok to finally aggregate the results to country scale, but would be good show also the non-aggregated results for all the results.
Thank you for the comment. The rainfed hazard/exposure was computed at grid cell level and the figures have been changed accordingly **(Fig. 02 and 03)**.

12. Fig. 5: Would be good to have the y and x axes in same scale, not to give misleading impression of the results. And/Or you could show 1:1 line, and with that it would be easier to see in which countries risk irrigated agriculture is higher/lower than in rainfed agriculture
Thanks for the comment. We changed the axes to normalized risk scores **(Fig. 05)**.

13. Page 7, Lines 170-173: Why is IH transformed logarithmically?
IH describes the volume of irrigation water needed additionally in drought periods. In most grid cells these volumes are relatively small but there are also some grids with extremely high values. In 569 out of the 26,478 irrigated grid cells the additional irrigation water requirement per drought event is lower than 100 m^3; in 1,450 grids it is lower than 1,000 m^3. These are grids with very small irrigated areas. However, there are also 95 grids where the additional irrigation water requirement per drought event is larger than 100,000,000 m^3. The logarithmic transformation accounted for the specific value distribution.

Referee #2 (Dr. Veit Blauhut)

Dear authors,firstly, please excuse my delay submitting this report. secondly, congratulations to avery well written piece of work. The papers reads very fluent and only leaves space for few questions.
Many thanks for the positive overall summary.

The authors are exploring agricultural drought risk on a global scale, comparing rainfed against irrigated agriculture in the frame of a conceptual model. I highly appreciate this unique attempt, especially the preceding expert survey. My major concern is a lack of validation e.g. with other global agricultural drought risk models and the "lacking"verification of the relevance of selected indicators. More data exists. Also quantitative approaches for validation exist. I please you to apply something that is not "visual comparison" (This really lowers the quality of your, apart from that, high quality paper)
To our knowledge, the analysis presents the first attempt to assess drought risk for agricultural systems at the global scale. Existing global analysis focus on drought risk in more general terms (e.g. Carrao et al., 2016, Dilley et al., 2005). Hence, a direct statistical comparison might be misleading - due to the different foci of the studies. We have visually compared our results to the work done by Carrao et al. (2016) and mention this in the discussion. An in-depth comparison and validation, while needed, would be a paper of its own. We added a few lines in the discussion **(P22, L531-534)** mentioning this as an outlook for future research.

Please find my more explicit comments in the PDF https://docs.google.com/document/d/19w7_cn6r4t3rKJxqq51H6I6veY6G5vZBLkgN-zUNbcs/edit
Many thanks, kindly find our responses below.

[a] P1 L20-21: A glimps if the assessment is of general risk information or applicable for early warning would be nice.
Thank you for the comment. The aim of this paper is to conduct a risk assessment for agricultural systems and not to focus on early warning/forecasting drought hazards. We believe that this is sufficiently clear from the abstract. No changes were made.

[b] P2 L49: I assume that you know what are you talking about BUT: please consider to cleary define risk relevant terminologies. Many terms are interpreted differently by schools, scientific field or even authors. Maybe a list/table in the appendix could do the job.

Thanks for the comment. This comment has been raised by the other reviewer as well. We follow the latest IPCC AR5 WGII (IPCC 2014) definitions of risk. We added a line **(P5, L115-116)** in the methods (chapter 2) on the risk concept that is used. Vulnerability and hazard were already defined (**P8, L209-2011; P4, L105-106**)

[c] P2 L65: Since you are setting a point on exposure I recommend to define this. Exposure is treated differently in drought risk community (from landuse to drought frequency)- thus a clarification is of need. Please see De Stefano et al. 2015 & Gonzales Tanago et al. 2016.

Many thanks, this comment is also related to the previous comment on definitions and has also been raised by the other reviewer. We follow the IPCC (2014) definition. We added a line in the methods (chapter 2.1; **P5, L115-116)** on how exposure is defined.

[d] P2 L65:Partly true. Dilley et al. 2005 and Li et al. 2017 also investigate at global scale. But using different/ and less vulnerability factors

Thanks for the suggestion, we added the paper from Dilley et al. (2005) to the introduction **(P3, L65)**. The paper by Li et al. (2017) has a geographic focus on Northwest China. Hence it was not mentioned in the introduction. We decided not to add it since the analysis is not global.

[e] P3 L72-75: You might also bring their "validation" schemes into play?

Thanks for the suggestion, Carrao et al. (2016) evaluated the robustness of their analysis to changes in indicator weights. Their model is based on an internal validation procedure that chooses the best model as the one giving regional vulnerability ranks that approximates the median of the ensemble among all models tested. Nevertheless, in this case the absence of reference data for performing an independent validation reduces the lack of effective testing options. A statistical validation of the sensitivity of the results towards changes in the input parameters (indicators, weights, normalization, aggregation methods), while needed, goes beyond the scope of this paper.

[f] P3 L77: I see the point, but not the matter for your research.

A social-ecological systems (SES) perspective is relevant when assessing drought risk for agricultural systems, which by definition have a strong social and ecological coupling. This point was also highlighted in a recent assessment of social-ecological systems vulnerability of deltaic regions confronted by multiple hazards - including droughts - by Hagenlocher et al. (2018).

[g] P3 L82: I question why a conceptual model should be "better" to analyse agricultural drought risk then a global analysis based on crop- models (such as Li et al 2009, Yin et al. 2014, Zhang...). Please explore the caveats of outcome related vs. conceptual models with the background of your, now published, drought risk review.

Here we used an integrated drought risk assessment approach based on the risk concept put forward by the IPCC WGII in their 5th Assessment Report (IPCC 2014). The advantage of such a conceptual model over an outcome oriented model (that estimates vulnerability indirectly by looking at losses) is that our approach allows for revealing drivers of risk (incl. vulnerability drivers) and hence entry points for vulnerability reduction whereas an outcome-based assessment approach does not allow for that. One strong advantage is that our approach provides comprehensive, aggregated, comparable and data-driven information on the actual vulnerability conditions and patterns at the global scale.

[h] P3 L82: What is an integrated drought risk assessment?

An integrated drought risk assessment combines drought hazard, exposure, and vulnerability by bringing together data from different sources and disciplines. We make that more clear in the text **(P3 L82-83)**.

[i] P4 L100: ??

The answer to this point is linked to the comment on [f], which was already addressed.

[j] P6 L140-143: This indeed is a little arbitrary. Of cause, most thresholds are subjective like this one. And I actually do not have a better idea, bit maybe you could provide some explanatory box/violine plots. Are there regional/ continental specifics? (appendix is fine)

In total there are 37,265 grid cells of the size 0.5 x 0.5 degree containing rainfed cropland. With the threshold of 10% selected for the present study, no drought at all would be observed in the period 1980-2016 in 3,999 grid cells (10.7%), mainly and very humid or cool climate. The number of grid cells without any drought would increase to 11,879 (31.9%) when using a threshold of 20% and to 20,803 grid cells (55.8%) when using a threshold of 30%. We decided, therefore, to keep the threshold of 10% we add some descriptive statistics on the effect of this threshold to the supplementary information **(Supplementary material (S5))**.

[k] P7 L170: Why?
Many thanks. This comment was already raised by "Reviewer 1" (see comment #13). IH describes the volume of irrigation water needed additionally in drought periods. In most grid cells these volumes are relatively small but there are also some grids with extremely high values. In 569 out of the 26,478 irrigated grid cells the additional irrigation water requirement per drought event is lower than 100 m^3; in 1,450 grids it is lower than 1,000 m^3. These are grids with very small irrigated areas. However, there are also 95 grids where the additional irrigation water requirement per drought event is larger than 100,000,000 m^3. The logarithmic transformation accounted for the value distribution.

[l] P8 L212-214: Again, please refer to Gonzales Tanago et al. 2016 and add some cons of this practise
Thanks for the suggestion. We have carefully read the paper by Gonzales Tanago et al. (2016), and it was already cited in the initial version of our manuscript. However, the authors do not mention specific limitations of index-based approaches. Hence for this point we decided not to refer to the paper. But we add some cons about this approach following suggestions by Naumann et al. (2018) and Beccari (2016) **(P8, L215 and P20, L461-464).**

[m] P9 L231: Similarity? Did you test this in the frame f a similarity test? Or Did you do cross-correlations? Please be more specific and consider to show your pre- selection criteria/ similarity tests, cross correlations. (again, appendix is fine)
Thank you for the comment. We agree that the sentence is not clear. The decision of which indicators to combine was not based on statistical similarity tests, but on "logical reasoning" due to what these indicators represent. For instance Agriculture (% of GDP) and Dependency on agriculture for livelihood (%) were combined under one income indicator and the variables GDP per capita, PPP and Population below the national poverty line (%) both refer to poverty and therefore combined in one integrated indicator. We have reframed the sentence and added which (and how) indicators were combined in the **P9**, **lines 234-237**.

[n] P11 L288: I'm aware that only few global datasets on drought impacts are available. With respect to the EM-DAT database regions like Europe are not well represented in the database. E.g. Spain and Northern Europe did not suffer a single drought event, Portugal maybe 2 ,etc. Thus, I question the reliability of this source and wonder why you did not compare to other global, maybe impact based, drought risk analysis.
We agree that the number in EM-DAT depends highly on data availability and the size of the country is important. We discussed these limitations in the manuscript (lines **402-408; 523-528**) and countries are mentioned as an example. Regarding the comparison with other drought risk analyses: To our knowledge, the analysis presents the first ever attempt to assess drought risk for agricultural systems at the global scale. Existing global analysis focus on drought risk in more general terms (e.g. Carrao et al., 2016, Dilley et al., 2005), and thus a direct comparison could be misleading due to the different foci. An in-depth comparison of existing global drought risk assessments goes beyond the scope of this paper. It could however be an interesting piece of work for future research. We added this as an outlook to the discussion **(P22, L531-534).** We also agree that calling this approach "validation" might be misleading, and hence change it to "comparison".

[o] P11 L292: Coming back here (just read the end): Your validation is of "visual nature". With respect to your own research (review paper) please consider to at least try to get some numbers behind your statements. Naumann et al. 2014 showed an easy approach to compare/validate relative pattern of vulnerability. This could also be done with the results of Carao et al.This way you could have to "different" datasets for validation
A direct numeric comparison is difficult due to the lack of an actual validation data set that represents the ground truth with adequately high spatial or temporal resolution. We decided to use EM-DAT because it systematically collects reports of drought events and drought impacts from various sources, including UN agencies, NGOs, insurance companies, research institutes and press agencies (**lines 291-292**). We added more about the point the referee is raising on the discussion, and mention the advantages and the need to have an in-depth statistical validation of drought events for future research **(P22, L531-534)**.

[p] P16 L379-381: This seems counter intuitive for me. E.g. a country for Iran is heavily depending on irrigation. The absurd overuse of groundwater within the last decade led to an extreme drop in groundwater levels, which in a next step, increases the vulnerability of the farmers. Of cause, this comes back to the lack of knowledge on the dynamics of vulnerability.
We agree with the comment. We added a line on vulnerability dynamics on the paragraph **(P16, L380)**.

[q] P20 L455: Did not see to many ecological vulnerability factors, only "Terrestrial and marine protected areas", soil erosion and fertilizer could also be shifted to technical and landuse, or?I would recommend not to highlight your research as social-ecological. (but it might be a matter of taste)

Thank you for the comment. Even if we moved them to another category, they still represent the environmental susceptibility of the country. Especially when assessing drought risk in the context of agricultural systems, which are by definition SES (Kloos and Renaud 2016), a SES perspective is of relevance. This point has been raised by the same reviewer before (see our response to comment [f]).

[r] P20 L461: I expected a more intense comparison

Many thanks. Our analysis has a distinct focus on agricultural systems, while Carrão et al. (2016) present a more generic drought risk assessment at the global scale. An in-depth statistical comparison of the findings hence might even be misleading due to the different foci of the analyses. We have, however, conducted a visual comparison of our findings and their findings. We added a paragraph on the discussion about the comparison between Carrão et al. (2016) and our paper (**P21, L478-492)**.

[s] P21 L493: But there are more data (modelled but..) Since you are not satisfied with EM-DAT, I do not understand why you did not use others.

This point is related to the one in the [o]. We decided to use EM-DAT because it systematically collects reports of drought events and drought impacts from various sources, including UN agencies, NGOs, insurance companies, research institutes and press agencies (lines **291-292**). We added more about the points the referee has been raising on the discussion, and mention the advantages and the need to have an in-depth statistical validation of drought events for future research (**P22, L531-534).**

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Global-scale drought risk assessment for agricultural systems

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Abstract

Droughts continue to affect ecosystems, communities, and entire economies. Agriculture bears much of the impact, and in many countries it is the most heavily affected sector. Over the past decades, efforts have been made to assess drought risk at different spatial scales. Here, we present for the first time an integrated assessment of drought risk for both irrigated and rain-fed agricultural systems at the global scale. Composite hazard indicators were calculated for irrigated and rain-fed systems separately using different drought indices based on historical climate conditions (1980-2016). Exposure was analyzed for irrigated and non-irrigated crops. Vulnerability was assessed through a social-ecological systems perspective, using social-ecological susceptibility and lack of coping capacity indicators that were weighted by drought experts from around the world. The analysis shows that drought risk of rain-fed and irrigated agricultural systems displays a heterogeneous pattern at the global level with higher risk for southeastern Europe, as well as northern and southern Africa. By providing information on the drivers and spatial patterns of drought risk in all dimensions of hazard, exposure, and vulnerability, the presented analysis can support the identification of tailored measures to reduce drought risk and increase the resilience of agricultural systems.

Keywords: Drought, Hazard, Exposure, Vulnerability, Rain-fed agriculture, Irrigated agriculture

1 Introduction

Droughts exceed all other natural hazards in terms of the number of people affected, and have contributed to some of the world's most severe famines (FAO, 2018; CRED and UNISDR, 2018). Drought is conceived as an exceptional and sustained lack of water caused by a deviation from normal conditions over a certain region (Tallaksen and Van Lanen, 2004, Van Loon et al., 2016). It can have manifold impacts on social, ecological, and economic systems, for instance agricultural losses, public water shortages, reduced hydropower supply, and reduced labor or productivity. While many sectors are affected by drought, agriculture's high dependency on water means it is often the first one of the most heavily affected sectors (Dilley et al., 2005; UNDRR, 2019). With nearly 1.4 billion people (18% of the global population) employed in agriculture, droughts threaten the livelihoods of many, and are hampering the achievement of the Sustainable Development Goals (SDGs) – notably SDG1 (no poverty), SDG2 (zero hunger), SDG3 (good health & well-being), and SDG15 (life on land). While there is ambiguity regarding global drought trends over~~in~~ the past century (Sheffield et al., 2012; Trenberth et al., 2013; McCabe and Wolock, 2015), drought hazards will likely increase in many regions in the coming decades (Sheffield and Wood, 2008; Dai, 2011; Trenberth et al., 2013; Spinoni et al., 2017; UNDRR, 2019, Spinoni et al., 2019b). Identifying pathways towards more drought resilient societies therefore remains a global priority.

Recent severe droughts in southeastern Brazil (2014-2017), California (2011-2017), the Caribbean (2013-2016), northern China (2010-2011), Europe (2011, 2015, 2018), India (2016, 2019), the Horn of Africa (2011-2012), South Africa (2015-2016, 2018), and Viet Nam (2016), have clearly shown that the risk of negative impacts associated with droughts is not only linked to the severity, frequency, and duration of drought events, but also to the degree of exposure, susceptibility and coping capacity of a given~~the~~ social-ecological system. Despite this, proactive management of drought risk is still not a reality in many regions across the world. Droughts and their impacts are still mostly addressed through reactive crisis management approaches, for example, by providing relief measures (Rojas, 2018). To improve the monitoring, assessment, understanding, and ultimately proactive management of drought risk effectively, we need to acknowledge that the root causes, patterns and dynamics of exposure and vulnerability need to be considered alongside climate variability in an integrated manner (Spinoni et al., 2019a; Hagenlocher et al., 2019).

Over the past decades, major efforts have been made to improve natural hazard risk assessments and their methodologies across scales, ranging from global risk assessments to local level assessments. At the global scale several studies have been published in recent years, focusing on the assessment of flood risk (Hirabayashi et al., 2013; Ward et al., 2013, 2014), seismic risk (Silva et al., 2018), cyclone risk (Peduzzi et al., 2012), or multi-hazard risk (e.g. Dilley et al., 2005; Peduzzi et al., 2009; Welle and Birkmann, 2015; Garschagen et al., 2016; INFORM, 2019; Koks et al., 2019; UNDRR, 2019). While major progress has been made regarding the mapping, prediction and monitoring of drought events at the global scale (e.g. Yuan and Wood, 2013; Geng et al., 2013; Spinoni et al., 2013, 2019b; Damberg and AghaKouchak, 2014; Hao et al., 2014; Carrão et al., 2017), very few studies have assessed either exposure to drought hazards (Güneralp et al., 2015) or drought risk at the global level (Carrão et al., 2016; Dilley et al., 2005). The study by Carrão et al. (2016) presents the first attempt to map drought risk at the global scale while considering drought hazard (based on precipitation deficits), exposure (population, livestock, crops, water stress), and societal vulnerability (based on social, economic and infrastructural indicators). While generic drought risk assessments are useful to get an overview of the key patterns and hotspots of drought risk, it is increasingly acknowledged that drought risk assessment should be tailored to the needs of specific users, so that management plans can be developed to reduce impacts (Vogt et al., 2018; UNDRR, 2019). Impact or sector specific assessments of who (e.g. farmers) and what (e.g. crops) is at risk to what (e.g. abnormally low soil moisture, deficit in rainfall, below average streamflow), where, and why, are needed to inform targeted drought risk reduction, resilience and adaptation strategies (IPCC, 2014). Such analyses are currently lacking. Furthermore, in their exposure analysis, Carrão et al. (2016) do not distinguish between rain-fed and irrigated agriculture, although different hazard indicators are relevant when assessing drought risk for these systems. In addition, the vulnerability analysis presented by Carrão et al. (2016) is based on a reduced set of social, economic and infrastructure-related indicators, and does not account for the role of ecosystem-related indicators as a driver of drought risk - a gap that was recently highlighted in a systematic review of existing drought risk assessments across the globe (Hagenlocher et al., 2019). A social-ecological systems perspective, especially when assessing drought risk in the context of agricultural systems, where livelihoods depend on ~~intact~~ ecosystems and their services, can help to better understand the role of ecosystems and their services as a driver of drought risk, but also as an opportunity for drought risk reduction (Kloos and Renaud, 2016).

This paper addresses some of the above gaps by presenting, for the first time, an integrated drought risk assessment that brings together data from different sources and disciplines for rain-fed and irrigated agricultural systems considering relevant drought hazard indicators, exposure and vulnerability at the global scale. The spatial variability of drought risk on global and regional scales might help to identify leverage points for~~in~~ reducing impacts and properly anticipate, adapt and move towards resilient agricultural systems.

2 Methods

Today, it is widely acknowledged that risk associated with natural hazards, climate variability and change is a function of hazard, exposure and vulnerability (IPCC, 2014; UNDRR, 2019). Following that logic, Figure 01 shows the overall workflow of the assessment, while the subsequent sections describe in detail how drought risk for agricultural systems, including both irrigated and rain-fed systems, were assessed at the global scale.

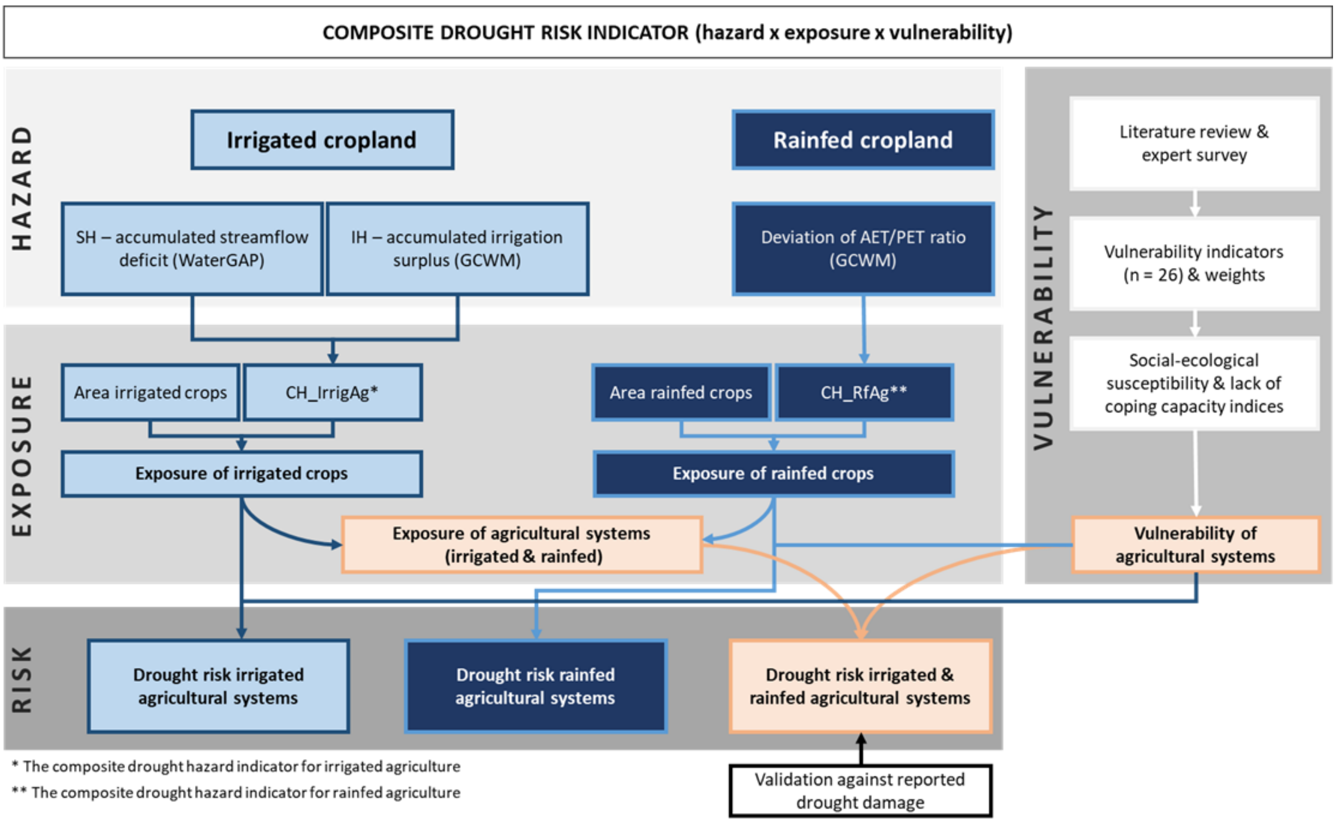


Fig 01. Workflow for the overall global drought risk assessment for agricultural systems (including irrigated and rain-fed systems).

The composite drought hazard indicators were calculated for irrigated and rain-fed systems separately using drought indices based on historical climate conditions (1980-2016), which resulted in integrated hazard maps for both rain-fed and irrigated agricultural systems, respectively. The different irrigated and non-irrigated crops by country were considered as the exposed element. Due to the lack of high-resolution gridded data on agricultural-dependent population at the global scale, this exposure indicator was not considered. The vulnerability component was assessed through a social-ecological systems (SES) lens, where social-ecological susceptibility and lack of coping capacity indicators were weighted by drought experts around the world.

2.1 Drought hazard and exposure indicators

The drought hazard indicators considered here represent the average drought hazard during the period 1980 to 2016 in each spatial unit for which it is computed. Drought hazard is defined as a deviation of the situation in a specific year or month from long-term mean conditions in the 30-year reference period from 1986 to 2015. To quantify drought hazard for such a long period, we used the global water resources and water use model WaterGAP (Müller Schmied et al., 2014) and the global crop water model GCWM (Siebert and Döll, 2010). The models simulate terrestrial hydrology (WaterGAP) and crop water use (GCWM) for daily time steps on a spatial resolution of 30 arc-minutes (WaterGAP) or 5 arc-minutes (GCWM). The most recent version WaterGAP 2.2d was forced by the WFDEI-GPCC climate data set (Weedon et al., 2014) which was developed by applying the forcing data methodology developed in the EU-project WATCH on ERA-Interim reanalysis data (Table 01). The GCWM used the CRU-TS 3.25 climate data set (Harris et al., 2014) as an input. CRU-TS 3.25 was developed by the Climate Research Unit of the University of East Anglia by interpolation of weather station observations and is provided as a time series of monthly values. Pseudo daily climate was generated by the GCWM as described in Siebert and Döll (2010). Following the definitions of the Intergovernmental Panel on Climate Change put forward in their Fifth Assessment Report (IPCC, 2014), exposure is -defined as the elements located in areas that could be adversely affected by drought hazard. The distinct exposure of irrigated and rain-fed agricultural systems to drought was considered by weighting grid cell specific hazards with the harvested area of irrigated and rain-fed crops according to the Monthly Irrigated and Rain-fed Cropping Areas (MIRCA2000) dataset (Portmann et al., 201~~0~~0) when aggregating grid cell specific hazards to exposure ~~for 412 MIRCA2000 units in subnational units for Argentina, Australia, Brazil, China, India, Indonesia and USA; and~~ at a national scale ~~elsewhere) or at country level~~. MIRCA2000 was also used to inform the models used in the hazard calculations about growing areas and growing periods of irrigated and rain-fed crops. The data set refers to the period centered around the year 2000; time series information is not available at the global scale. To maximize the representativeness of the land use, the reference period and evaluation period used in this study were centered around the year 2000.

Table 01. Hazard and exposure indicators used in the analysis and their processed data

Risk component	**Composite indicator**	**Indicator**	**Processed data**
Drought hazard	CH_IrrigAg	Accumulated streamflow deficit	WaterGAP (1980-2016) with climate forcing WFDEI-GPCC. Streamflow monthly time series.
		Accumulated irrigation surplus	GCWM (1980-2016) with climate forcing CRU TS3.25. Monthly time series of net irrigation requirements
	CH_RfAg	AET/PET deviation ratio	GCWM (1980-2016) with climate forcing CRU TS3.25. Annual time series of the deviation of the ratio AET / PET from the long-term (1986-2015) median of the ratio AET / PET
Exposed elements	Rainfed & irrigated	Aggregation of pixel level data to national scale	MIRCA 2000 dataset was used to compute harvested area weighted averages of the indicators

2.1.1 Irrigated agricultural systems

The composite drought hazard indicator is defined as the product of mean severity and frequency of drought events. F~~f~~or irrigated agriculture (*CH_IrrigAg*) it combines an indicator for streamflow drought hazard (*SH*), i.e. for abnormally low streamflow in rivers, with an indicator of abnormally high irrigation water requirement (*IH*) (Fig. 01). It thus considers the deviations of both demand and supply of water from normal conditions. *SH* and *IH* are computed with a spatial resolution of 0.5° by 0.5° (55 km by 55 km at the equator). Greenland and Antarctica are excluded. As *IH* is not meaningful in grid cells without irrigation, *CH_IrrigAg* is only computed for grid cells in which irrigated crops are grown according to MIRCA2000 (Portmann et al., 201~~0~~0).

IH was calculated by using the GCWM based on a monthly time series of net irrigation requirements from 1980 to 2016. The net irrigation requirement is the volume of water needed to ensure that the AET of irrigated crops is similar to their PET. (Fig. 01). The calculations were performed for 487,121 grid cells with a resolution of 5 arc-minutes containing irrigated crop areas and then aggregated to 26,478 grid cells with a 30 arc-minute resolution to be consistent with the resolution used by WaterGAP. *SH* was calculated by using WaterGAP based on a monthly time series of streamflow from 1980 to 2016 in 66,896 0.5° grid cells world-wide.

For both *IH* and *SH*, drought hazard per grid cell was quantified as the product of a (scaled or transformed) mean severity of all drought events during the evaluation period 1980-2016 and the frequency of drought events during this period. Drought events for *IH* and *SH* were determined independently. In the case of *IH* computation, a drought event starts as soon as the monthly irrigation requirement exceeds the irrigation requirement threshold and ends when the surplus reaches zero. In the case of *SH* computation, a drought starts if the monthly streamflow drops below the streamflow threshold and ends as soon as the deficit reaches zero. For each grid cell and each of the 12 calendar months, a drought threshold was defined as the median of the variable values in the respective calendar month during the reference period 1986-2015. To avoid spurious short droughts and drought interruptions, it was defined that 1) a drought event starts with at least two consecutive months with an IH surplus or a SH deficit and 2) one month without an IH surplus or if a SH deficit does not break the event (Spinoni et al., 2019a). The accumulated surplus (*IH*) / deficit (*SH*) during each drought event is the severity of the drought event. Mean severity is computed as the arithmetic average of the severity of all drought events during the evaluation period. As in case of *SH* the deficit and thus the severity of streamflow drought is strongly correlated with the mean annual streamflow, mean severity is therefore scaled by dividing the accumulated streamflow deficit by mean annual streamflow. In this way scaled mean streamflow drought severity is expressed as fraction of the mean annual flow volume that is on average missing during drought events. In the case of *IH*, mean severity is transformed logarithmically before computation of *IH*.

The composite drought hazard indicator for irrigated agriculture *CH_IrrigAg* was then calculated for each grid cell by combining the streamflow hazard *SH* and irrigation requirement hazard *IH*. To ensure that both indicators are weighted equally, their native values were first scaled to a range between 0 and 1 by dividing *SH* and *IH* in each grid cell by the maximum *SH* or *IH* detected globally. The frequency distribution of the *SH* values calculated that way was shifted to the left with a mean of 0.244 while the frequency distribution of *IH* was shifted to the right with a mean of 0.664. Therefore, *CH_IrrigAg* was calculated for each grid cell as:

$$CH\_IrrigAg = 0.5\left(SH/\underline{SH} + IH/\underline{IH}\right) \qquad (01)$$

with *SH* being the grid cell specific streamflow hazard, *IH* being the grid cell specific irrigation requirement hazard and $\underline{SH}$ and $\underline{IH}$ being the mean of *SH* or *IH* calculated across all grid cells.

The exposure of irrigated agricultural systems to drought at ~~subnational (402 MIRCA2000 units) and~~ national scale was derived as the harvested area weighted mean of the *CH_IrrigAg* across all grid cells belonging to the respective aggregation units.

2.1.2 Rain-fed agricultural systems

The composite drought hazard indicator for rain-fed agriculture (*CH_RfAg*) was quantified based on the ratio of actual crop evapotranspiration (AET - in m^3 day^{-1}) to potential crop evapotranspiration (PET in m^3 day^{-1}), calculated for the evaluation period 1980-2016 and compared to the reference period 1986-2015 (Fig. 01). PET quantifies the water requirement of the crop without water limitation while AET refers to the evapotranspiration under actual soil moisture conditions.

The GCWM was applied for 24 specific rain-fed crops and the two groups "others annual" and "others perennial" to calculate crop specific AET and PET on a daily time step. Together, the 24 crops and two crop groups cover all crop species distinguished by FAO in their database FAOSTAT. The sum of daily crop specific AET and PET was calculated for all crops and for each year in the period 1980-2016 for 927,857 grid cells containing rainfed cropland and aggregated to 37,265 grid cells with the resolution 0.5 x 0.5 degree.

~~MIRCA2000 units. This procedure accounted for the differences in growing areas of the specific rain-fed crops across grid cells belonging to the same MIRCA2000 unit and therefore reflects the different exposure of specific crops in different parts of the MIRCA2000 unit to drought.~~

The mean ratio between AET and PET ($\underline{AET/PET}$) for the reference period 1986-2015 was then calculated for each grid cell ~~MIRCA2000-unit~~. $\underline{AET/PET}$ reflects long-term water limitations for the geographic unit with low values representing~~for~~ high aridity and high values for low aridity. *CH_RfAg* was then determined by calculating the ratio AET/PET for each year from 1980-2016, and by deriving the percentile of a relative difference of 10% to the long-term mean ratio $\underline{AET/PET}$ from the time series. Consequently, *CH_RfAg* reflects the probability for the occurrence of a drought year in which the ratio between total AET and total PET across all rain-fed crops is 10% lower than the long-term mean ratio $\underline{AET/PET}$. We also tested other percentage thresholds (20%, 30%, 50%), but for many parts of the world we never computed reductions of the ratio AET/PET by more than 10% of the long-term mean ratio (Supplementary (S5)). Therefore, it was decided to use the 10% threshold consistently.

2.1.3 Integration of drought exposure of irrigated and rain-fed cropping systems

The combined drought exposure for rain-fed and irrigated cropping systems was evaluated ~~for the 402 MIRCA2000-units and~~ at country level by averaging the harvested area weighted drought exposure of irrigated and rain-fed cropping systems. As described before, distinct methods were used to calculate hazard and exposure of irrigated and rain-fed systems so that a direct comparison of the exposure values is not meaningful. In addition, the frequency distributions differed considerably, with a harvested area weighted global mean of the drought exposure of 0.45~~4~~5 for irrigated systems and 0.189~~24~~ for rain-fed systems. To ensure a more similar weight of rain-fed and irrigated drought exposure, ~~the MIRCA2000-unit~~country specific exposures were divided by the global mean, and then the integrated exposure was calculated as harvested area weighted mean:

$$Exp_{tot} = \left(\left(AH_{rf} \star Exp_{rf} \;/\; 0.189\cancel{24}\right) + \left(AH_{irr} \star Exp_{irr} \;/\; 0.45\cancel{4}5\right)\right) / \; AH_{tot} \tag{02}$$

with Exp_{tot}, Exp_{rf}, and Exp_{irr} being the exposure of the whole, rainfed and irrigated cropping systems ~~(both rain-fed and irrigated cropping systems)~~ to drought and AH_{tot}, AH_{rf}, and AH_{irr} being the harvested area of all crops, rainfed crops and irrigated crops ~~(both rain-fed and irrigated crops)~~.

~~For countries with sub-national resolution of the MIRCA2000-units, the exposure of the whole cropping system to drought at country level was then calculated as the harvested area weighted mean across Exp_{tot} of the MIRCA2000-units belonging to the specific countries.~~

2.2 Vulnerability and risk assessment

According to the Intergovernmental Panel on Climate Change (IPCC) (2014), vulnerability is the predisposition to be adversely affected as a result of the sensitivity or~~and~~ susceptibility of a system and its elements to harm, coupled with a lack of coping and adaptive capacity. The assessment of drought vulnerability is complex because it depends on both biophysical and socioeconomic drivers (Naumann et al., 2014). Due to this complexity, the most common method to assess vulnerability in the context of natural hazards and climate change is using composite indicators or index-based approaches (Beccari, 2016; Sherbinin et al., 2019). Although their usefulness for policy support has also been subject to criticism (Hinkel, 2011, Beccari 2016), it is widely acknowledged that composite indicators can identify generic leverage points for reducing impacts at the regional to global scale (Sherbinin et al., 2017, 2019; UNDRR 2019).

Following the workflow to calculate composite indicators proposed by the Organisation for Economic Co-operation and Development (OECD, 2008) and Hagenlocher et al. (2018), the methodological key steps on which the vulnerability assessment is based are: 1) definition of the conceptual framework, 2) identification of valid indicators, 3) data acquisition and pre-processing, 4) analysis and imputation of missing data, 5) detection and treatment of outliers, 6) assessment of multicollinearities, 7) normalization, 8) weighted aggregation, and 9) visualization.

An initial set of vulnerability indicators for agricultural systems was identified based on a recent review of existing drought risk assessments (Hagenlocher et al., 2019). In total 64 vulnerability indicators, including social, economic, physical, farming practices, environmental, governance, crime and conflict factors, were selected and classified by social-ecological susceptibility (*SOC_SUS*, *ENV_SUS*), lack of coping capacity (*COP*) and lack of adaptive capacity (*AC*) following the risk framework of the IPCC (IPCC, 2014). Indicator weights, which express the relevance of the identified indicators for characterizing and assessing the vulnerability of agricultural systems to droughts, were identified through a global survey of relevant experts (n = 78) around the world; the majority of whom have worked in academia and for governmental organizations with more than five years of work experience (Meza et al., 2019). In total, 46 of the 64 indicators were considered relevant by the experts, comprising susceptibility, coping and adaptive capacity indicators. However, since adaptive capacity is only relevant when assessing future risk scenarios and less relevant to current risk, indicators related to adaptive capacity and indicators that could be measured with the same data source due to their similarity in what they represent were removed. For instance *Agriculture (% of GDP)* and *Dependency on agriculture for livelihood (%)* were averaged into one income indicator and the variables *GDP per capita, PPP* and *Population below the national poverty line (%)* both refer to poverty, and therefore were also averaged to a combined indicator. This resulted in a set of 26~~36~~ indicators as part of the vulnerability assessment (Table 02~~1~~).

Following data acquisition, the data were pre-processed by transforming absolute to relative values and standardized when necessary (e.g. travel time to cities ≤30 min (population), divided by the total population). Descriptive statistics were used to evaluate the degree of missing data. The imputation of missing values was done with data from previous years and using secondary sources following Naumann et al. (2014) in cases where the *r* value lay between -1.0 to -0.9 or 1.0 to 0.9 using a Spearman correlation matrix and scatter diagram for visual interpretation. Following suggestions by Roth et al. (1999), Peng et al. (2006) and Enders (2003), listwise and pairwise deletion thresholds were selected when >30% of data were missing on a country level and when > 20% of data were missing on the indicator level. After the deletion, 168 countries and 26 indicators were considered for the final analysis. To detect potential outliers, scatter plots and box plots for each indicator were created. Potential outliers were further examined using triangulation with other sources and past years. On this basis, outliers were identified in only one indicator (i.e. fertilizer consumption (kg/ha of arable land)) and treated using winsorization following Field (2013). Multicollinearities were identified using a Spearman correlation matrix for the different vulnerability components (social susceptibility, environmental susceptibility and lack of coping capacity). Following the rule proposed by Hinkle et al. (2003), any values higher than $r > 0.9$ or smaller than $r < -0.9$ were considered very highly correlated. The correlation was considered only if it was significant at the 0.05 level (2-tailed). Two indicators for the lack of coping capacity component and two from social-susceptibility (e~~i~~.eg. *healthy life expectancy at birth (years)*, and *disability-adjusted life*) showed high and significant correlations. However, no indicators were excluded on this basis, due to the difference in concepts they represented and their relevance at global level. In order to render the indicators comparable, the final selected indicators were normalized to a range from 0 to 1 using min-max normalization (Naumann et al., 2014; Carrão et al., 2016):

$$Z_i = X_i - X_{min} \,/\, X_{max} - X_{min} \qquad (03)$$

where Z_i is the normalized score for each indicator score X_i. For variables with negative cardinality to the overall vulnerability the normalization was defined as:

$$Z_i = 1 - (X_i - X_{min} \,/\, X_{max} - X_{min}) \qquad (04)$$

Finally, the normalized indicator scores were aggregated into vulnerability components (*SOC_SUS*, *ENV_SUS*, *COP*) using weighted arithmetic aggregation based on (using the example of *SOC_SUS*):

$$SOC\_SUS = \sum W_i \, Z_i \qquad (05)$$

where W_i are the weights for each normalized dataset, and Z_i are the weights as obtained from the global expert survey. Thereby, weights were normalized to add up to 1. The final indicators and their respective weights are listed in Table 02~~1~~. The vulnerability components of social-ecological susceptibility (*SE_SUS*) were combined using an average, which was then combined with lack of coping capacity (*COP*) to obtain a final vulnerability index (*VI*) score:

$$VI = V(SE\_SUS) + V(COP) / 2 \qquad (06)$$

Table 0~~1~~2. Vulnerability indicators used in the analysis and their related expert-weights*.

Indicator	Data source	Weight*
Social susceptibility (SOC_SUS)		
Share of GDP from agr., forestry and fishing in US$ (%)	FAO (2016)	0.96
Rural population (% of total population)	World Bank (2011-2017)	0.85
Prevalence of undernourishment (% of population)	World Bank (2015)	0.82
Literacy rate, adult total (% of people ages 15 and above)	World Bank (2015)	0.80
Prevalence of conflict/insecurity (Crime and Theft, Index (0-30))	World Bank (2017)	0.76
Proportion of population living below the national poverty line (%)	SDG indicators (2015-2017)	0.75
Access to improved water sources (% of total population with access)	World Bank/FAO (2015)	0.66
DALYs (Disability-Adjusted Life Years)(DALYs per 100,000, Rate)	GBD (2016)	0.65
GINI index	World Bank (2017)	0.64
~~Agricultural machinery, tractors per 100 sq. km of arable land~~	~~World Bank (2009)~~	~~0.63~~
Insecticides and pesticides used (ton/ha)	FAO (2016)	0.63
Gender Inequality Index	UNDP (2018)	0.62
Electricity production from hydroelectric sources (% of total)	World Bank (2015)	0.62
Unemployment, total (% of total labor force) (national estimate)	World Bank (2017)	0.60
Dependency ratio (Population ages 15-64 (% of total population))	World Bank (2011-2016)	0.60
Population using at least basic sanitation services (%)	WHO (2015)	0.60
Healthy life expectancy (HALE) at birth (years)	WHO (2014)	0.56
Ecological susceptibility (ECO_SUS)		
Average land degradation in GLASOD erosion degree	FAO (1991)	0.92
Fertilizer consumption (kilograms per hectare of arable land)	World Bank (2015)	0.74
Average soil erosion	FAO (1991)	0.72
Terrestrial and marine protected areas (% of total territorial area)	World Bank (2016-2017)	0.63
Lack of coping capacity (COP)		
Saved any money in the past year (% age 15+)	Global FINDEX (2014-2017)	0.87
Government Effectiveness: Percentile Rank	World Bank (2017)	0.85
Total dam storage capacity per capita. Unit: m3/inhab	FAO Aquastat (2017)	0.82
Total renewable water resources per capita (m3/inhab/year)	FAO (2014)	0.76
Corruption Perception Index (CPI)	Transparency International (2017)	0.68
Travel time to cities ≤30 min (population) (%)	JRC (2015)	0.65

290 ** derived from a global expert survey (Meza et al., 2019)*

The final drought risk index (DRI)~~-~~ (Fig. 01) was calculated by multiplying the indices for drought hazard/exposure and vulnerability~~., when the analysis was performed at pixel level (irrigated agricultural system). In contrast, when the analysis was performed at aggregated level, hazard/exposure was multiplied with vulnerability to calculate risk (MIRCA2000 units to~~

~~country level) (rain-fed agricultural system)~~. At pixel level, the presence of hazard and vulnerability point to a certain drought risk, independent of how much crop area is contained in the specific pixel. At aggregated level, the different crop areas in the specific pixels must be considered; therefore exposure was calculated as harvested area weighted mean of the pixel level hazard and then multiplied with vulnerability to calculate drought risk at country level.

The total drought risk score for irrigated and rain-fed systems combined (DRI_{tot}) is derived by multiplying the exposure of the whole cropping system Exp_{tot} (Equation 02) with the vulnerability index *VI*.

2.3 Comparison~~Validation~~ against drought impact data

The outcomes of the risk assessment for irrigated and rain-fed systems combined (DRI_{tot}) were compar~~validat~~ed against impact data from the international Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters (CRED) using visual correlation (Fig. 06). EM-DAT systematically collects reports of drought events and drought impacts from various sources, including UN agencies, NGOs, insurance companies, research institutes and press agencies. Here, the number of drought events within the period 1980-2016 was used as an input for the comparison~~validation~~. Thereby, a drought event is registered in EM-DAT when at least one of the following criteria applies: 10 or more people dead; 100 or more people affected; declaration of a state of emergency or a call for international assistance.

3 Results

This section presents the results of the global drought risk assessment for agricultural systems (irrigated and rain-fed) at pixel level (Fig. 02 and 03) and for the total risk of both systems combined at national resolution (Fig. 04).~~ The drought risk for irrigated and rainfed agricultural systems is presented at 0.5 degrees (Fig. 02) and at national resolution (Fig. 04)., while drought risk for rain-fed systems is presented for MIRCA2000-units (at sub-national resolution for USA, Brazil, Argentina, China, India, Australia and Indonesia; national resolution elsewhere (Fig. 03); and at national resolution (Fig. 04). Drought risk for all crops (irrigated and rain-fed) is shown at national resolution (Fig. 04) and for MIRCA2000-units (Fig. 06).~~ The patterns colored dark red show high levels of the different risk components, while the dark blue colors reflects low scores of the different risk components.

3.1 Drought risk for irrigated agricultural systems

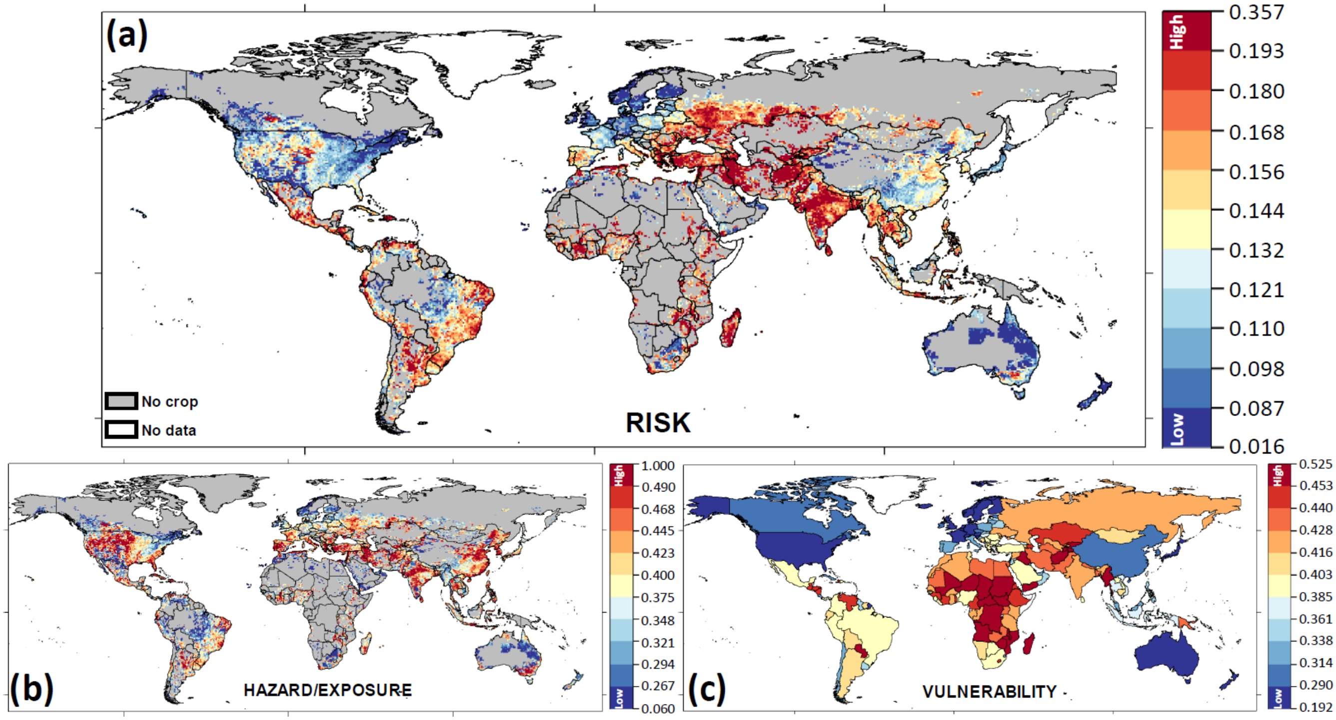
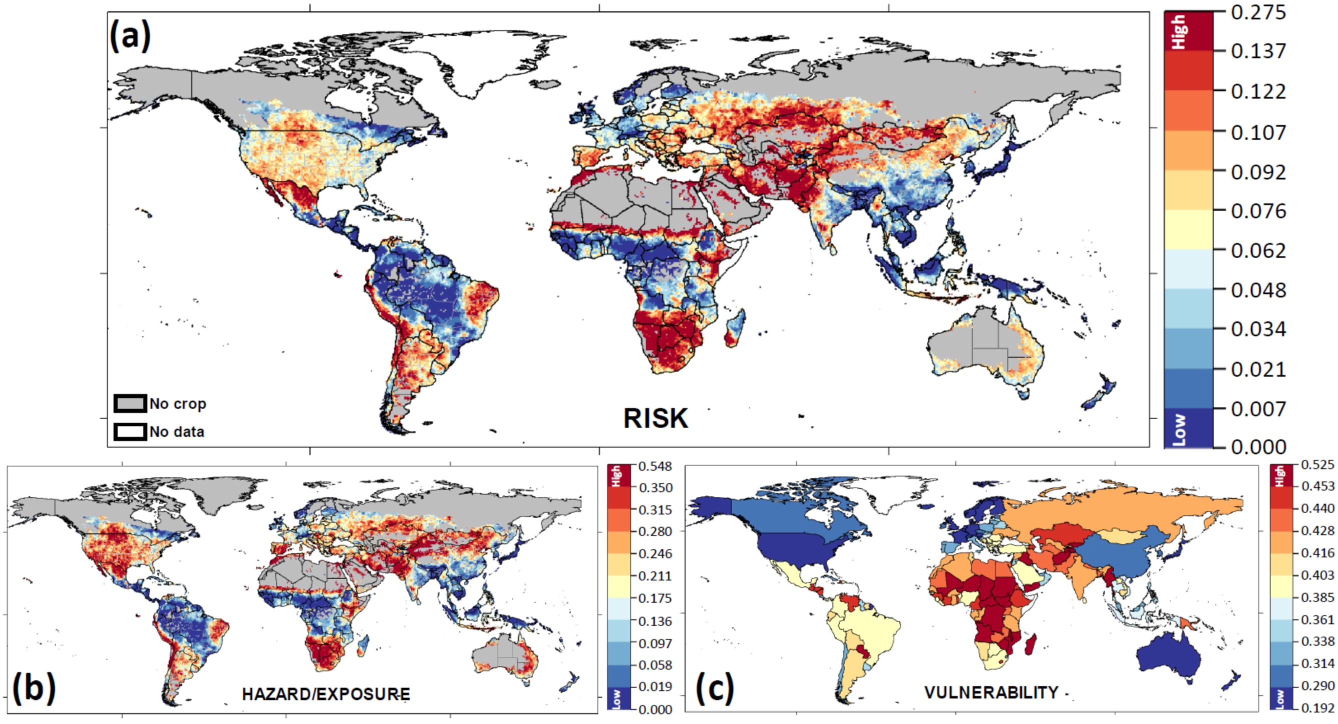


Fig 02. Drought risk (a), hazard/exposure (b) and vulnerability (c) for irrigated agricultural systems. The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest blue color, and by determining the class ranges of the other colors by linear interpolation. Risk was directly calculated by multiplying hazard with vulnerability (pixel-level analysis).

The drought risk for irrigated agricultural systems varies significantly among continents and countries. Especially large countries such as USA, Brazil, China and Australia show a high variation at country level, due to varying climatic conditions. Drought hazard/exposure was highest in regions with a high density of irrigated land and high irrigation water requirements such as the western part of USA, central Asia, northern India, northern China and southern Australia. Vulnerability was high particularly in sub-Saharan Africa but also in some countries in central Asia and the Middle East region and low in general for industrialized and high income countries. The combination of hazard and vulnerability to risk resulted in highest values for large parts of west, central and south Asia, eastern Africa and the eastern part of Brazil. Low risk areas include western Europe, USA, Australia and most parts of China (Fig. 02).

3.2 Drought risk for rain-fed agricultural systems


(a)
No crop
No data
RISK
High
Low
0.275
0.137
0.122
0.107
0.092
0.076
0.062
0.048
0.034
0.021
0.007
0.000
(b)
HAZARD/EXPOSURE
0.548
0.350
0.315
0.280
0.246
0.211
0.175
0.136
0.097
0.058
0.019
0.000
(c)
VULNERABILITY
0.525
0.453
0.440
0.428
0.416
0.403
0.385
0.361
0.338
0.314
0.290
0.192

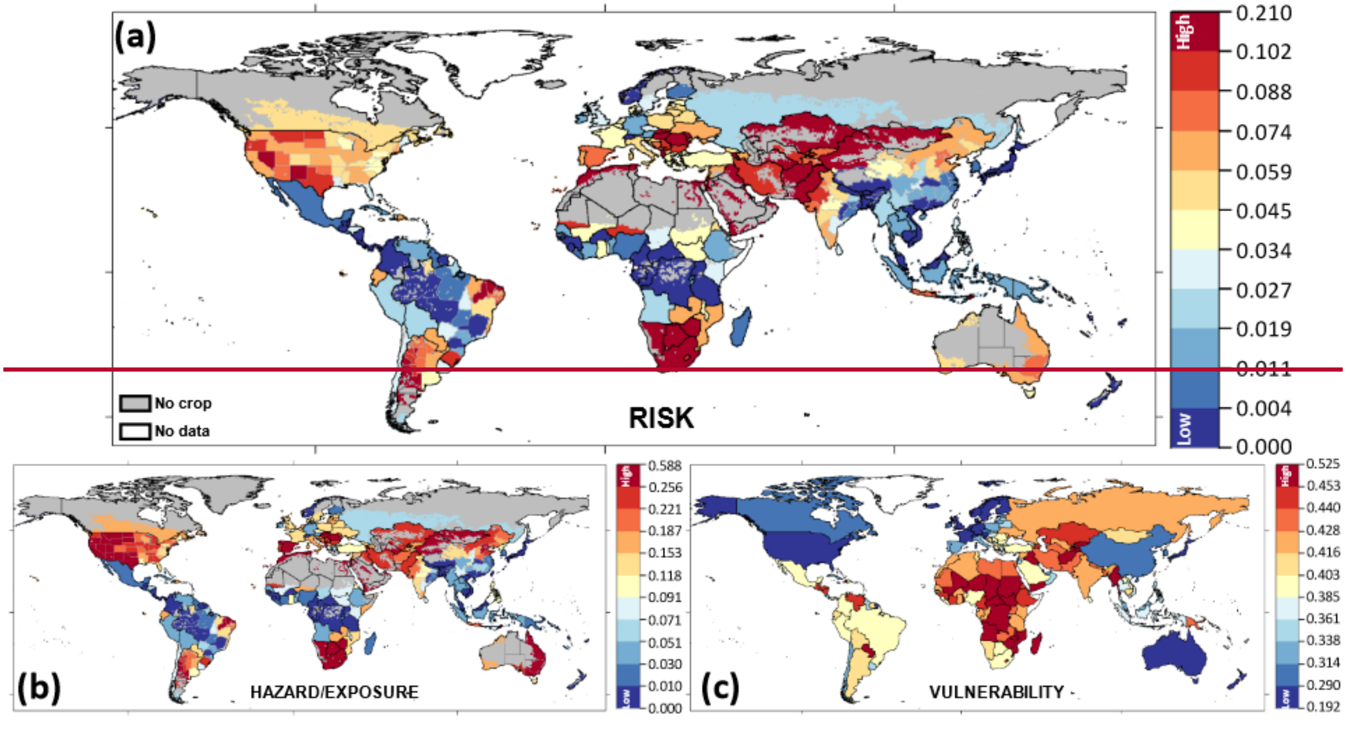

(a)
No crop
No data
RISK
High
Low
0.210
0.102
0.088
0.074
0.059
0.045
0.034
0.027
0.019
0.011
0.004
0.000
(b)
HAZARD/EXPOSURE
0.588
0.256
0.221
0.187
0.153
0.118
0.091
0.071
0.051
0.030
0.010
0.000
(c)
VULNERABILITY
0.525
0.453
0.440
0.428
0.416
0.403
0.385
0.361
0.338
0.314
0.290
0.192

Fig 03. Drought risk (a), hazard/exposure (b) and vulnerability (c) for rain-fed agricultural systems. The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest blue color and by determining the class ranges of the other colors by linear interpolation. Risk was calculated by multiplying hazard/exposure with vulnerability (pixel level analysis ~~at aggregated MIRCA2000 units~~).

~~Rain-fed drought hazard/exposure and drought risk are computed at national level, except for selected larger countries, such as Australia and USA, where a subnational division is applied.~~ High levels of risk (dark yellow to red color scheme) for rain-fed agricultural systems are observed in southern Africa, southeastern Europe, northern Mexico, northeast Brazil, at the western coast of South America, southern Russia and western Asia. ~~The top three hazard/exposure countries are United Arab Emirates, Oman and Bahrain (the latter two also possessing high vulnerability scores), meanwhile the United Arab Emirates performed better on social-ecological susceptibility, which resulted in lower drought risk values.~~

The vulnerability to drought highlights the relevance to increase the coping capacity of the countries in order to reduce their overall drought risk. For instance, Australia, despite being highly exposed to drought hazard, has low socio-ecological susceptibility and high enough coping capacities to considerably reduce the overall drought risk.

3.3 Drought risk for agricultural systems (irrigated and rain-fed combined)

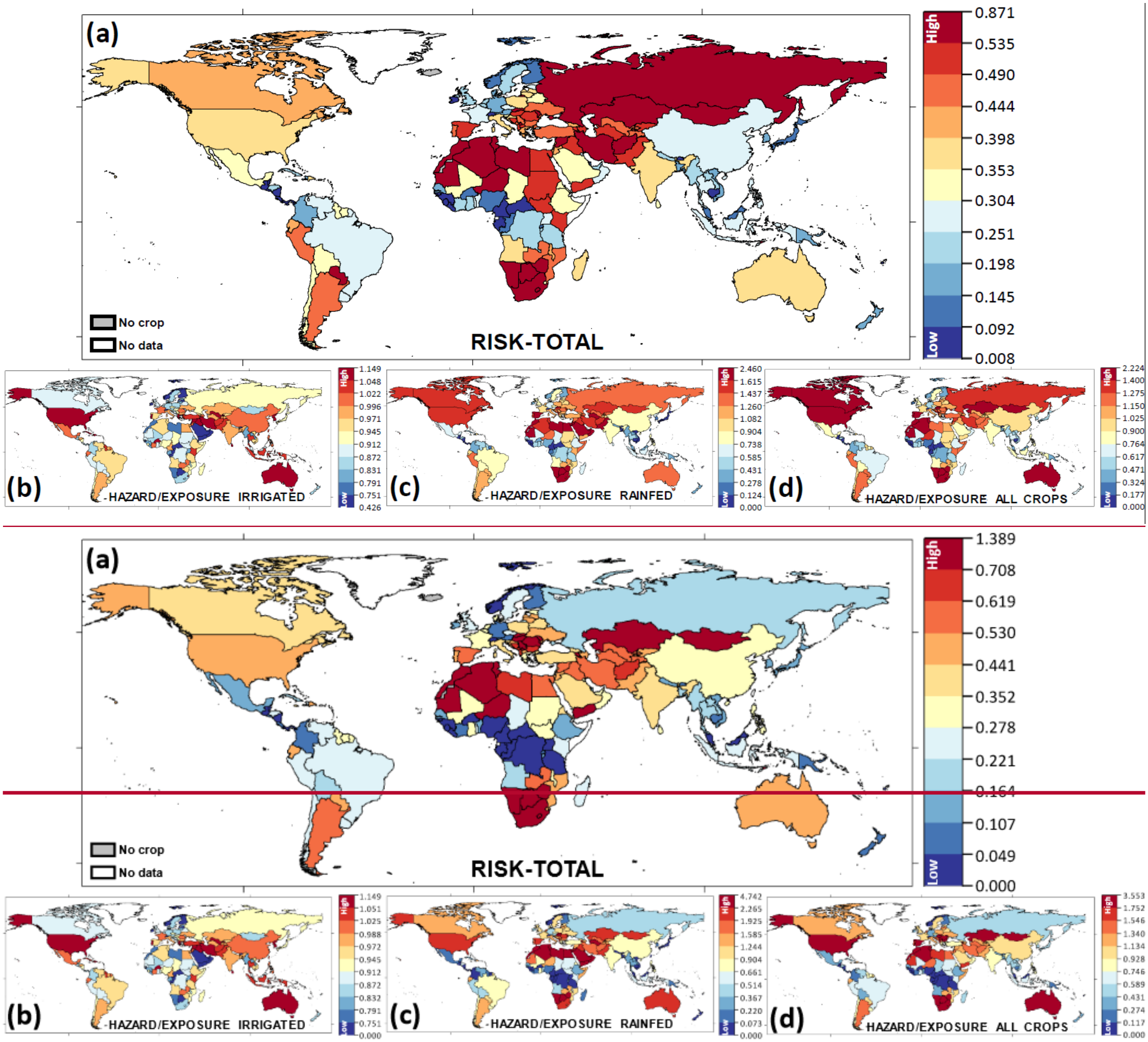


Fig 04. Drought risk (a), hazard/exposure of irrigated (b), rain-fed (c), and the whole crop production sector (d). The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest blue color, and by determining the class ranges of the other colors by linear interpolation. Risk was calculated by multiplying hazard/exposure with vulnerability shown in Fig. 02c and 03c.

The hazard/exposure maps shown in ~~the~~ Figure 04 are slightly different to the ones shown in Figures 02 and 03 due to the aggregation at country level. The analysis shows that regions with low hazard/exposure of rain-fed and irrigated crops to drought tend to be tropical ~~semi-arid~~ and subarctic regions following the Köppen-Geiger climate classification (1980-2016) (Beck et al., 2018). There are significant regional differences when comparing irrigated and rain-fed drought hazard/exposure. For instance, the northern part of Latin America and Central Africa have low hazard/exposure levels, given the humid climate conditions resulting in a low total risk, even though those regions are characterized by high vulnerability levels. Southern Africa, however, has a high amount of drought-exposed rain-fed crops, but a lower vulnerability compared to other African countries. Despite this, risk scores in that region are very high. Very high drought hazard/exposure and vulnerability levels can be found in the Middle East and Northern Africa.

Although the drought hazard was computed differently for the different agricultural systems, the countries with high risk of drought to both farming systems are Botswana, Namibia and Zimbabwe (Fig. 02 and 03), these countries share the same relevant indicators that define their high vulnerability: high soil and land degradation rate, low literacy rate, and low total renewable water (Supplementary (S3)). Table 0~~2~~3 shows the top and bottom ten countries with the highest/lowest total drought risk (DRI_{tot}) as well as their hazard/exposure and vulnerability scores.

Table 0~~2~~3. Rank of countries with the highest and lowest risk of drought for combined agricultural systems (rain-fed and irrigated)

Country	**Drought risk (countries rank)**	**Risk score total**	**Hazard/Exposure**			**Vulnerability score**
			Haz/Exp irrigated	**Haz/Exp rain-fed**	**Haz/Exp total**	
Zimbabwe	1	0.871	0.967	1.885	1.804	0.483
Namibia	2	0.846	0.769	2.122	2.061	0.411
Botswana	3	0.811	0.466	2.095	2.076	0.391
Morocco	4	0.786	0.774	2.172	1.873	0.419
Kosovo	5	0.728	0.936	1.871	1.854	0.393
East Timor	6	0.701	0.971	1.882	1.854	0.378
Mauritania	7	0.692	0.886	1.670	1.580	0.438
Lesotho	8	0.692	0.840	1.562	1.556	0.445
Kazakhstan	9	0.670	0.974	1.573	1.499	0.447
Algeria	10	0.636	0.969	1.595	1.492	0.426
Guatemala	158	0.039	0.857	0.026	0.087	0.446
Gambia	159	0.037	0.760	0.093	0.094	0.394
Belize	160	0.035	0.943	0.079	0.093	0.375

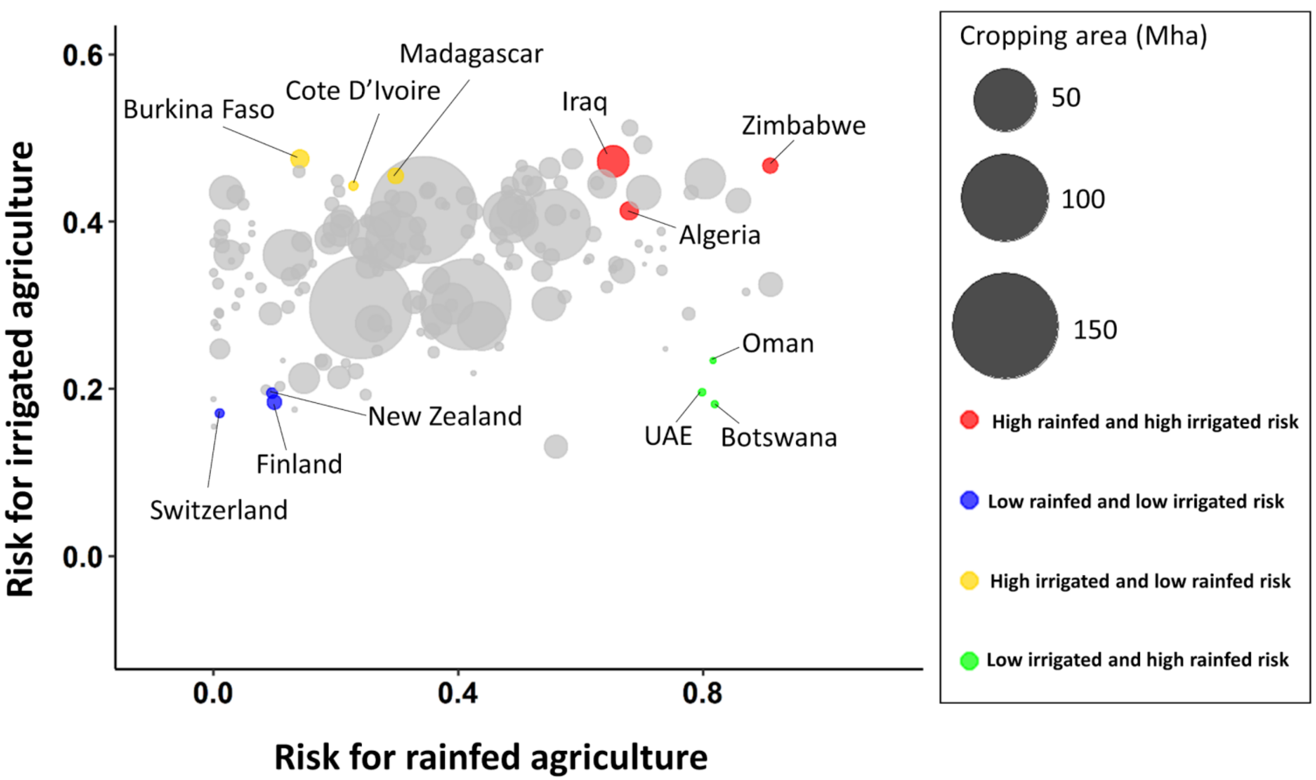
Sierra Leone	161	0.023	0.934	0.005	0.057	0.402
Brunei	162	0.020	0.741	0.000	0.077	0.254
Guinea	163	0.019	0.822	0.033	0.042	0.452
Switzerland	164	0.017	0.695	0.046	0.068	0.247
Guinea-Bissau	165	0.017	0.723	0.026	0.042	0.401
Fiji Islands	166	0.011	0.833	0.017	0.033	0.329
Central African Republic~~AR~~	167	0.008	0.646	0.016	0.016	0.505

~~Country~~	~~Drought risk (countries rank)~~	~~Risk score total~~	~~Hazard/Exposure~~			~~Vulnerability score~~
			~~Haz/Exp irrigated~~	~~Haz/Exp rain-fed~~	~~Haz/Exp total~~	
~~Botswana~~	~~1~~	~~1.389~~	~~0.466~~	~~3.589~~	~~3.553~~	~~0.391~~
~~Namibia~~	~~2~~	~~1.219~~	~~0.769~~	~~3.073~~	~~2.969~~	~~0.411~~
~~Zimbabwe~~	~~3~~	~~1.155~~	~~0.967~~	~~2.532~~	~~2.394~~	~~0.483~~
~~Algeria~~	~~4~~	~~1.12~~	~~0.969~~	~~2.952~~	~~2.626~~	~~0.426~~
~~Morocco~~	~~5~~	~~1.102~~	~~0.774~~	~~3.129~~	~~2.626~~	~~0.419~~
~~East Timor~~	~~6~~	~~1.043~~	~~0.971~~	~~2.815~~	~~2.757~~	~~0.378~~
~~Armenia~~	~~7~~	~~0.95~~	~~0.987~~	~~3.048~~	~~2.290~~	~~0.415~~
~~Hungary~~	~~8~~	~~0.907~~	~~0.932~~	~~2.516~~	~~2.476~~	~~0.366~~
~~Tunisia~~	~~9~~	~~0.886~~	~~0.949~~	~~2.460~~	~~2.184~~	~~0.406~~
~~Yemen~~	~~10~~	~~0.867~~	~~0.613~~	~~2.323~~	~~1.652~~	~~0.525~~
~~Republic of the Congo~~	~~152~~	~~0.006~~	~~0.741~~	~~0.008~~	~~0.014~~	~~0.426~~
~~Belize~~	~~153~~	~~0.006~~	~~0.943~~	~~0.000~~	~~0.016~~	~~0.375~~
~~Fiji~~	~~154~~	~~0.005~~	~~0.833~~	~~0.000~~	~~0.016~~	~~0.329~~
~~Guinea~~	~~155~~	~~0.004~~	~~0.822~~	~~0.000~~	~~0.009~~	~~0.452~~
~~Burkina Faso~~	~~156~~	~~0.003~~	~~1.114~~	~~0.000~~	~~0.007~~	~~0.426~~
~~Vanuatu~~	~~157~~	~~0~~	~~No crop~~	~~0.000~~	~~0.000~~	~~0.388~~
~~Uganda~~	~~158~~	~~0~~	~~0.798~~	~~0.000~~	~~0.000~~	~~0.434~~
~~Gambia~~	~~159~~	~~0~~	~~0.760~~	~~0.000~~	~~0.001~~	~~0.394~~
~~D. R. C.~~	~~160~~	~~0~~	~~0.886~~	~~0.000~~	~~0.001~~	~~0.459~~
~~C. A. R.~~	~~161~~	~~0~~	~~0.646~~	~~0.000~~	~~0.000~~	~~0.505~~

Seven out of the ten countries with the highest overall drought risk are located on the African continent. However, Kosovo, East Timor and Kazakhstan ~~Armenia, Yemen and Hungary~~ also possess high risk levels (Table 03~~2~~). Zimbabwe~~Botswana~~ ranks as the country with the highest drought risk mainly due to its high exposure combined with its ~~relatively~~ high vulnerability (S1).

In general, the countries that present higher drought risk have a high amount of exposed crops. Vulnerability varies among them, with Zimbabwe~~Yemen~~ being the country with the highest vulnerability. The lack of coping capacity and social-ecological susceptibility were determinant factors for countries like Botswana~~Yemen~~ and Zimbabwe (S1). There were cases where countries such as Namibia presented high socio-ecological susceptibility in contrast with high coping capacity, reducing its overall vulnerability. The drought risk in countries such as ~~Afghanistan and Venezuela~~Lesotho and Mauritania that have in contrast limited coping capacities, is notably higher (S1). The analysis also reveals that, although risk is currently close to zero in several countries (e.g. Fiji Islands~~DRC~~, C.A.R., Guinea-Bissau~~Uganda,~~ etc.), this could rapidly change once these countries are affected by droughts given their very high vulnerability.

The comparison of the drought risks of rain-fed and irrigated cropping systems (Fig. 05) shows that several countries such as Zimbabwe, Iraq and Algeria are exposed to high risk for both cropping systems. These countries are frequently hit by drought and similarly have a high vulnerability to drought (Fig. 02 and 03). In contrast, countries such as Switzerland, Finland and New Zealand are characterized by low drought hazard/exposure for irrigated and rain-fed systems and low vulnerability to drought (Fig. 02 and 03). In countries such as Botswana, Oman and the United Arab Emirates, drought risk is high for rain-fed cropping systems but low for irrigated cropping systems (Fig. 05). These countries are defined by arid climate conditions exposing rain-fed crops to high risk while the drought risk for irrigated cropping systems is low because of relatively low interannual variability in climatic conditions resulting in low variability of irrigation water requirement and streamflow, their risk is also determined by their different vulnerability dynamics (e.g. hydroelectric sources, retain renewable water). In contrast, drought risk for irrigated cropping systems is high and drought risk of rain-fed cropping systems is small in countries such as Burkina Faso, Madagascar and Cote D'Ivoire (Fig. 05). In these~~all~~ three countries, there is a big variability in climatic conditions with irrigated crops being cultivated in the more arid parts of the country and rain-fed crops in more humid parts. In addition, aquatic crops with a high water demand such as rice and sugarcane, are the most commonly cultivated irrigated crops in these countries (Frenken, 2005).



Risk for irrigated agriculture
0.6
0.4
0.2
0.0
Risk for rainfed agriculture
0.0
0.4
0.8
Burkina Faso
Cote D'Ivoire
Madagascar
Iraq
Zimbabwe
Algeria
Oman
UAE
Botswana
New Zealand
Finland
Switzerland
Cropping area (Mha)
50
100
150
High rainfed and high irrigated risk
Low rainfed and low irrigated risk
High irrigated and low rainfed risk
Low irrigated and high rainfed risk

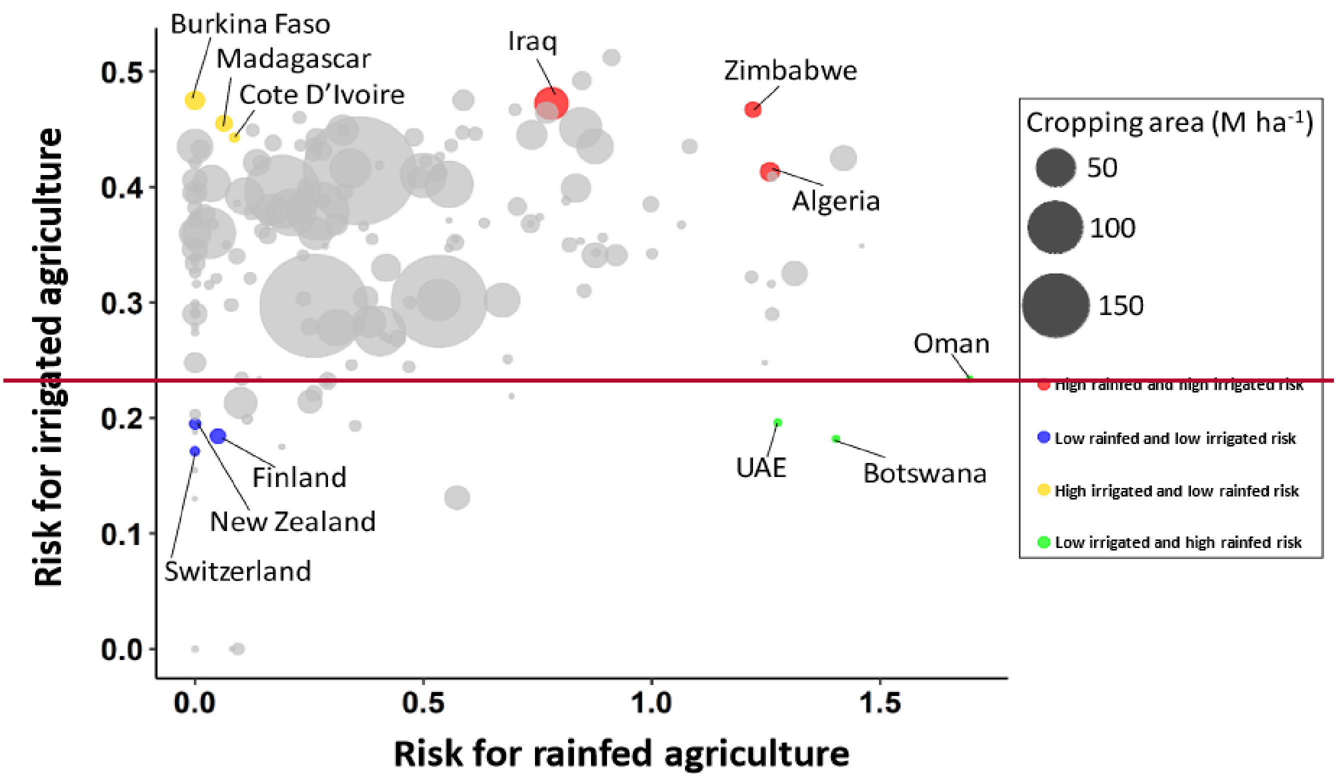
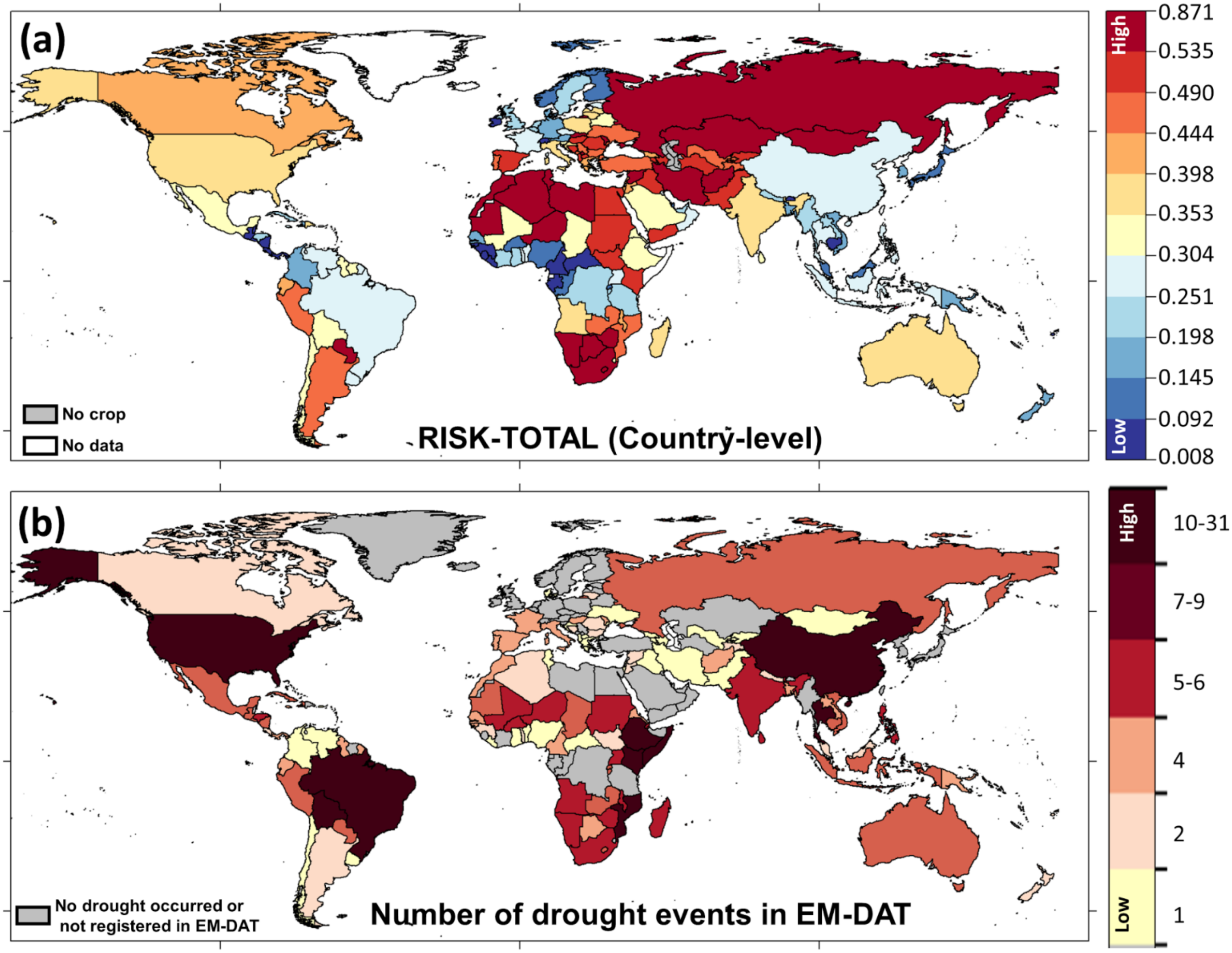
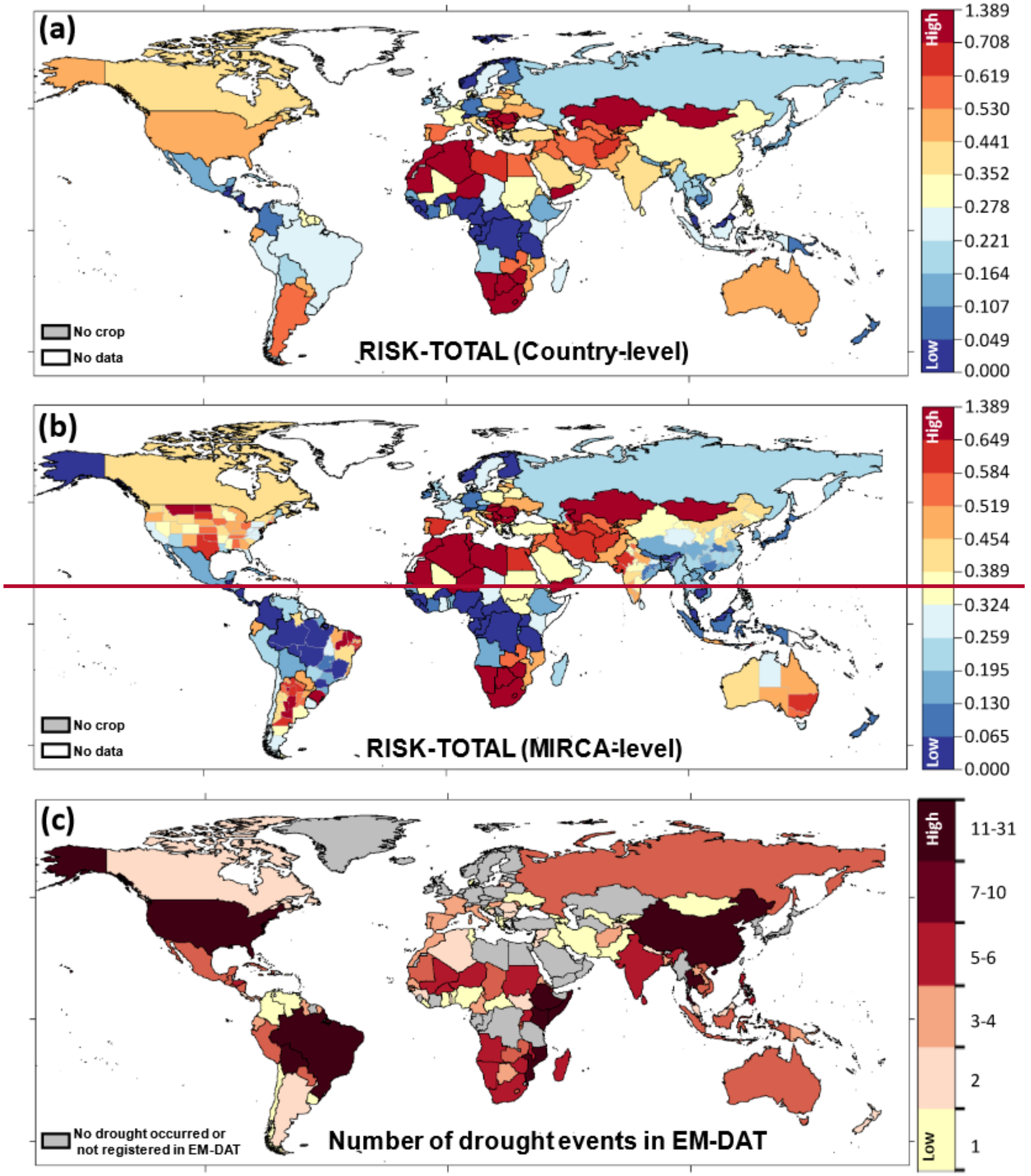


Fig. 05 Country profiles contrasting the drought risk of irrigated and rain-fed agricultural systems. The size of the bubbles indicates the crop growing area (sum of rain-fed and irrigated areas per country in Million ha~~, based on MIRCA units~~).

3.4 Comparison~~Validation~~

The comparison of drought risk (DRI_{tot}) with drought events registered in EM-DAT shows good agreement in many countries. For countries which have low drought risk such as the countries in tropical Africa, northern and western Europe or countries in the northern part of South America, there is either none or just one drought registered in EM-DAT (Figure 06a, 06b~~e~~). There is also good agreement for countries in southern Africa and some countries in the African transition zone ~~northwest Africa~~ with very high drought risk and many registered drought events and for countries with intermediate drought risk such as Canada, Australia or Italy~~Spain~~. However, some disagreement between calculated risk and the number of reported drought events is acknowledged. For instance, Brazil is not showing high agreement between EM-DAT and the country risk level, even though the eastern part of the country presents a high risk for irrigated and rainfed systems (Fig. 2 and 3), total drought risk level is affected by the other regions with lower risk in the country. The same occurs in other ~~several~~ large countries such as USA, ~~Brazil,~~ Russia, China and India, the calculated drought risk is low or intermediate although a large number of drought events have been registered in EM-DAT. The reason for this disagreement is that the risk shown in Figure 06a is representative for the whole country while drought events which only have local or regional impacts are also registered in EM-DAT (see Sect. 2.3). For all these big countries, we detected considerable spatial heterogeneity with regard to drought risk where regions with high drought risk such as the central part of USA, northeast Brazil, northern China and ~~,~~ northwest India ~~and southern Russia~~ are complemented with other regions of low drought risk (Fig. 06a~~b~~).~~-~~. Therefore, the high number of registered drought events in EM-DAT is corroborated by the presence of high regional drought risk (Fig. 2 and 3).


(a)
High
Low
0.871
0.535
0.490
0.444
0.398
0.353
0.304
0.251
0.198
0.145
0.092
0.008
No crop
No data
RISK-TOTAL (Country-level)
(b)
High
Low
10-31
7-9
5-6
4
2
1
No drought occurred or
not registered in EM-DAT
Number of drought events in EM-DAT



440

Fig 06. Comparison~~Validation~~ of total risk against drought impact data

4 Discussion

The present study performs, for the first time, a separate global drought risk analysis for irrigated and rain-fed cropping systems, including regions that indicate a high vulnerability to droughts and are particularly exposed. In previous assessments, the share of irrigated cropland was either ignored or considered as a vulnerability indicator (Carrão et al., 2016). The drought hazard analysis is based on three indicators: streamflow drought hazard (*SH)*, abnormally high irrigation water requirement (*IH*), and a composite drought hazard indicator for rain-fed agriculture (*CH_RfAg)*, which quantify drought as a deviation from normal conditions consistent with common definitions. In agreement with the results for drought hazard obtained by Carrão et al. (2016), the largest drought hazard is obtained for arid and semi-arid regions such as northern and southern Africa, northern Mexico~~southeastern Europe~~, along the coastline of Peru and Chile, the Arabian Peninsula and Mongolia for rain-fed systems, Italy, Turkey and Western Mexico for irrigated systems, and the western USA, northeast Brazil, western Argentina, central Asia, Middle East countries, western India, northern China and southern Australia for both irrigated and rain-fed systems. ~~For irrigated systems this includes Italy, Turkey and Western Mexico, whilst for both irrigated and rain_fed systems this represents the western USA, northeast Brazil, western Argentina, central Asia, Middle East countries, western India, northern China and southern Australia.~~ In contrast, previous studies based on standardized indices such as the SPI have detected the highest drought hazard mainly in humid regions such as central Europe, southeast Asia, southern Brazil and tropical Africa (Geng et al., 2015). The reason for this difference could be that deviations from normal conditions should not be treated similarly for arid and humid regions as not every precipitation or streamflow deficit in humid regions will automatically become a hazard for cropping systems. In fact, in humid regions, crops often perform better in relatively dry years (Holzkamper et al., 2015). We account for these effects by normalizing streamflow deficits with long-term mean annual river discharge (*SH*) or by calculating the probability of reductions in the AET/PET ratio of rain-fed crops in relative terms (*CH_RfAg*).

In the present study, the rain-fed hazard is computed as the probability of a 10% decline in the AET/PET ratio compared to long-term mean conditions, whereas the irrigated drought hazard represents the combination of severity and frequency values derived from streamflow or irrigation water requirement (see Sect. 2). While the methodology reflects well the common understanding of the factors most influential for drought hazard in the two cropping systems, a direct numerical comparison of the calculated hazard for rain-fed and irrigated systems is not meaningful. The hazards and exposure calculated in this study should be used to rank or compare countries within the rain-fed or irrigated domain but not in between. The reasoning for the calculation of the total exposure and risk in this study was less to support comparisons across countries but to account for the different extend of irrigated and rainfed systems within the specific countries. There are countries in which crop production is completely rainfed and countries in which all crops are irrigated so that only the risk for the rainfed or irrigated systems are relevant. Except from these extremes, crop production in most countries is either predominantly irrigated or predominantly rainfed. We account for this by calculating total crop exposure to drought (Fig. 04d) as the harvested area weighted mean of the exposures of irrigated crops (Fig. 04b) and of the rainfed crops (Fig. 04c). Our attempt to calculate hazard, exposure and risk for the whole crop production sector by assigning a similar weight to the hazard-exposures for rain-fed and irrigated systems must be viewed critically and results should be taken with care. A potential way to derive specific weights for rain-fed and irrigated exposure could be validating calculated hazard and exposure, but also vulnerability and risk, with information about drought impacts separately, for both irrigated and rain-fed systems. Lack of data for drought impacts distinguishing rain-fed and irrigated systems was the main reason why this approach was not implemented for the current study.

The calculation of the drought hazard of irrigated cropping systems in this study is based on the two components streamflow hazard (*SH*) and irrigation requirement hazard (*IH*) reflecting water supply (*SH*) and water demand (*IH*) of irrigated systems. Therefore we do not consider specifically in our approach the availability and use of groundwater resources for irrigation. It is well agreed that dynamics in streamflow are usually larger than dynamics in groundwater storage, so that groundwater is used by many farmers to substitute temporary deficits in surface water supply for irrigation systems. In general, access to groundwater should therefore be considered to reduce drought hazard ~~for~~ and vulnerability of irrigated cropping systems. Consideration of groundwater resources would, however, require dynamic quantification of groundwater storage and groundwater levels, which is challenging for global scale analyses and not possible with the models applied in this study. In addition, more conceptual work is needed to decide which degree of temporal variability in groundwater levels constitutes a hazard and how to treat long-term depletion of groundwater resources (negative trends) in drought risk studies.

The multi-dimensional nature of vulnerability of agricultural systems is represented by a set of 26 expert-weighted indicators.~~,~~ One of the major limitations of this data driven approach is the spatial detail information for computing the model, however, at a global level it is not feasible to get a harmonized dataset of all the proxy variables, but some caution must be advised when zooming in at the subnational level (Naumann et al. 2018). When interpreting the results, it is necessary to consider that some highly correlated indicators were maintained in the analysis as they present different drivers of vulnerability and hence different entry points for vulnerability reduction. The selected indicators comprises~~ing~~ social, economic, environmental, physical, and governance-related factors contributing to social-ecological susceptibility and the lack of coping capacity. In doing so, the present study goes beyond existing global drought risk assessments (Carrão et al., 2016) which are based on equal weights and do not consider relevant environmental vulnerability indicators as a driver of drought risk. The latter, however, is relevant when assessing drought risk for agricultural systems, where factors such as land degradation or soil erosion are shown to exacerbate drought risk (Hagenlocher et al., 2019). In future assessments an alternative to the expert-based weighting of vulnerability indicators chosen here could be the use of statistical approaches (e.g. Principal Component Analysis) to identify relevant indicators. However, given the high number of experts who participated in the weighting exercise (n = 78) the expert-based approach seems more suitable to identify relevant indicators as compared to an approach that builds on statistical significance only. Further, Hagenlocher et al. (2013) evaluated the outcomes of PCA-based and expert-based indicator choice on a composite vulnerability index, and did not find major differences.

~~Nevertheless, t~~The findings of the drought risk assessment presented here correspond to a certain degree to the findings of Carrão et al. (2016).~~,~~ Although the focus of the current paper is more explicitly on agriculture, both studies present methodological similarities. In Carrão et al. (2016) the percentage crop land per grid-cell is one factor in the exposure analysis and the percentage irrigated agricultural land is one of the vulnerability factors. Although Carrão et al. (2016) include other factors such as population density, livestock density and baseline water stress in the analysis, the results give a high weight to the risk for agriculture. In both studies the regions less affected by droughts correspond to the regions with low or no exposure for agriculture and population (e.g. deserts and tropical forests). This is mainly the case in Amazonia and Central Africa. Also, similarities between areas of high levels of risk are evident, including southern and eastern Europe, the Eurasian steppe, northern Africa and the Middle East, northeastern Brazil and south eastern South America.

Similarities are also found for the risk of irrigated agricultural systems. Examples are irrigated croplands in India, the United States and Australia. Differences in the overall patterns are due to the separation of irrigated and non-irrigated agriculture in the current study and the aggregated exposure information in Carrão et al. (2016). In an updated version of the risk map from Carrão et al. (2016), using a higher resolution population database and grid level exposure information, as shown in Vogt et al. (2018, Figure 7) similarities are even more evident.

~~who also found southern and northern Africa as well as the Middle East to be severely at risk. Moreover,~~ However, the present study includes a spatially explicit model of AET for the main crop types of two different agricultural systems (irrigated and rain-fed agriculture), and includes a specialized vulnerability index for this sector according to expert judgment. These differences have revealed the importance to ~~be impact~~ focus~~ed~~ more clearly on distinct impacts (e.g. on irrigated vs rainfed systems) when conducting ~~on~~ drought risk assessments, even within the same sector. For instance, irrigated agricultural systems in Latin America are highly exposed to droughts, whereas the probability of droughts occurring in rain-fed agricultural systems in that region is comparably low.

D~~However, d~~espite these advancements, the presented analysis does have limitations. First, due to the lack of up to date land use data on irrigated vs. rain-fed agriculture at global scale, the exposure analysis is based on MIRCA data from the year 2000 (Portmann et al., 201~~0~~0). Given that cropping systems are subject to change, this adds uncertainty to the results. ~~Drought exposure in large countries with variable climate conditions such as Russia and Canada needs to be viewed critically, since drought exposure is significantly higher in some parts of these countries when conducting the analysis at provincial or pixel level. For instance, China shows a high variation in exposure levels in the eastern and western parts of the country when analyzed at pixel level (Fig. 02 and 03).~~ Second, data used for the vulnerability analysis stems from different sources which makes it difficult to evaluate the inherent uncertainties in the data. Third, the data is not consistently available for all countries for the same years (Table 02~~1~~). Fourth, the vulnerability analysis is based on nation-state resolution data, which does not allow for mapping spatial variability in vulnerability at the sub-national level. Fifth, applying expert opinions to weight drought vulnerability indicators according to their relevance brings subjectivity to the assessment, which necessitates a strong network of relevant experts. Sixth, preventive/adaptive planning requires going beyond evaluating drivers of risk and mapping current patterns of risk. Future scenarios of drought risk, considering both changing environmental and climate conditions as well as possible future socio-economic development pathways, are needed in order to anticipate future challenges.

Future research should address these challenges by also investigating sub-national patterns in vulnerability, and developing future drought risk scenarios in all dimensions of drought hazards, exposure, and vulnerability. In addition, attempts to investigate changes and trends in drought risk and risk components are highly needed to better understand trajectories of drought risk in different countries and for the whole world. Further, inherent uncertainties, as well as the sensitivity of the risk assessment outcomes towards changes in the input parameters (e.g. indicator choice and weighting), should be investigated and validated statistically. This gap has also been highlighted in a recent review of climate vulnerability assessments (Sherbinin et al., 2019) in general, as well as in a recent review of drought risk assessments (Hagenlocher et al., 2019) in particular.

The comparison~~validation~~ conducted in this study, has shown that there is limited data available on agricultural losses and impacts caused by droughts at the global level. Furthermore, impacts are not always direct, as droughts can have cascading indirect impacts (Freire-Gonzales et al., 2017; Van Lanen et al., 2017) which are difficult to assess. In addition, for countries where we find high drought risk (e.g., Mongolia, Iran, Kazakhstan and the countries in southeast Europe), no or very few drought events are registered in EM-DAT. The reason for this mismatch could be that drought events in these countries were not registered in EM-DAT. For example, in Romania, EM-DAT reports two drought events while according to other reports, twelve years between 1980 and 2012 were classified as drought years with 48% of the agricultural land affected (Lupu et al., 2010; Mateescu et al., 2013). On top of this, in Iran, EM-DAT reports one drought event while other sources recounted several droughts during 1980-2005, with the most extreme drought lasting for four years from 1999 to 2002 (Javanmard et al., 2017; Zoljoodi and Didevarasl, 2013). These examples suggest that it cannot be concluded from missing drought records in EM-DAT that specific countries were not affected by drought. Once improved and reliable impact data is available at the global scale, future research should also focus on the statistical validation of drought risk assessments with drought events and impact data. Ongoing efforts of countries to report their losses and impacts due to natural hazards (e.g. as part of the Sendai Monitoring) are considered as a first important step towards that direction.

Lastly, while this study presents the first attempt to assess drought risk for agricultural systems, more work is needed to analyze drought risk for other sectors, such as public water supply, tourism, energy production, and water-borne transport, among others.

5 Conclusions

This paper presents, for the first time, a global-scale drought risk assessment for both irrigated and rain-fed agricultural systems from a social-ecological perspective by integrating drought indicators for hazard, exposure, and vulnerability. It goes beyond previous studies by including a separated and spatially explicit analysis of the drought hazard and exposure for irrigated and rain-fed agricultural systems, as well as an empirically-based weighting of vulnerability indicators. The latter being based on the judgment of drought experts around the globe. The presented methodology can serve as a framework for the analysis of other affected sectors, such as ~~e.g.~~ water or energy. Findings from this study underscore the relevance of analyzing drought risk from a holistic perspective (i.e., including the sector-specific hazard, exposure and vulnerability) and based on a spatially explicit approach. By providing information on high risk areas and underlying drivers, this approach helps to identify priority regions as well as entry points for targeted drought risk reduction and adaptation options. While this first attempt provides valuable information at the global level, improvements could be achieved with the availability of more spatially explicit vulnerability information (i.e. at sub-national levels) and the availability of standardized drought impact information that can serve for a quantitative validation of risk levels.

6 Acknowledgments

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