



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
20 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.
25 The analysis shows that drought risk of rain-fed and irrigated agricultural systems displays 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.

30 **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



35 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
40 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 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.

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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
50 of 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
55 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
60 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
65 (Carrão et al., 2016). 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



70 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
75 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
80 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).



85 This paper addresses some of the above gaps by presenting, for the first time, an integrated drought risk assessment 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 in reducing
impacts and properly anticipate, adapt and move towards resilient agricultural systems.

2 Methods

90 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.



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. 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). 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., 2000) 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.

2.1.1 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 $\text{m}^3 \text{ day}^{-1}$) to potential crop evapotranspiration (PET in $\text{m}^3 \text{ day}^{-1}$), calculated for the evaluation period 1980-2016 and compared to the reference period 1986-2015. 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 and aggregated to 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 (AET/PET) for the reference period 1986-2015 was then calculated for each MIRCA2000-unit. AET/PET reflects long-term water limitations for the geographic unit with low values 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. Therefore, it was decided to use the 10% threshold consistently.

2.1.2 Irrigated agricultural systems

The composite drought hazard indicator for irrigated agriculture ($CH_IrrigAg$) 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). 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., 2000).

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. 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



170 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*.**

175 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:

180

$$CH_IrrigAg = 0.5(SH/\underline{SH} + IH/\underline{IH}) \quad (01)$$

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.

185 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.

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

190 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 0.445 for irrigated systems and 0.124 for rain-fed systems.

195 To ensure a more similar weight of rain-fed and irrigated drought exposure, the MIRCA2000-unit specific exposures were divided by the global mean, and then the integrated exposure was calculated as harvested area weighted mean:

$$Exp_{tot} = \left((AH_{rf} * Exp_{rf} / 0.124) + (AH_{irr} * Exp_{irr} / 0.445) \right) / AH_{tot} \quad (02)$$



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

205 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 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), 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).

215 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.

220 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** were removed. This resulted in a set of 36 indicators as part of the vulnerability assessment (Table 01).

235 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 240 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 245 (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 (i.e. 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. 250 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):

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

255 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:

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

260 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):

$$SOC_SUS = \sum W_i Z_i \quad (05)$$



265 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 01. 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:

270
$$VI = V(SE_SUS) + V(COP) / 2 \quad (06)$$

Table 01. 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
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* derived from a global expert survey (Meza et al., 2019)

275 The final drought risk index (DRI) was calculated by multiplying the indices for drought hazard 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
280 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.

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 .

285 2.3 Validation against drought impact data

The outcomes of the risk assessment for irrigated and rain-fed systems combined (DRI_{tot}) were validated 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 collect reports of drought events and drought impacts from
various sources, including UN agencies, NGOs, insurance companies, research institutes and press agencies. Here, the number
290 of drought events within period 1980-2016 was used as an input for the 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) (Fig. 02
295 and 03) and for the total risk of both systems combined (Fig. 04). The drought risk for irrigated 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
300 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

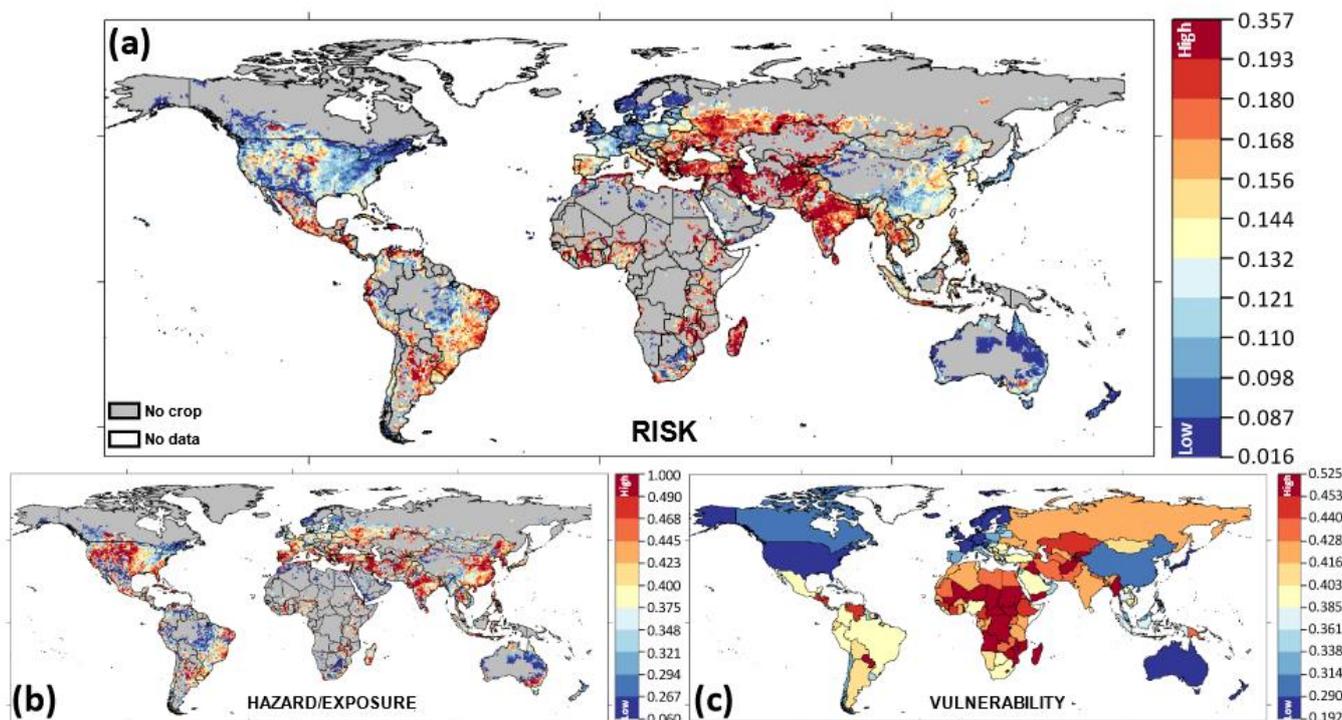
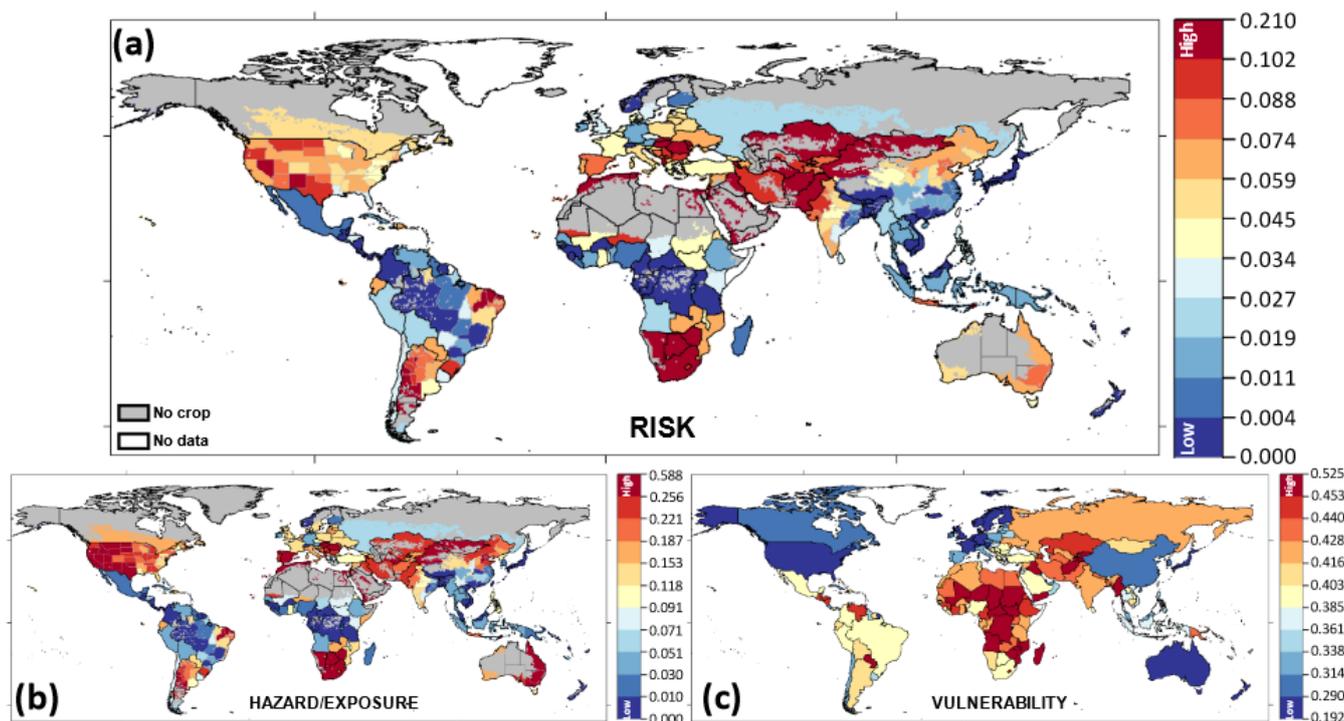


Fig 02. Drought risk (a), hazard/exposure (b) and vulnerability (c) for irrigated agricultural systems. The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest blue color, 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



320 **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 (analysis at aggregated MIRCA2000-units).

325 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 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.

330 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.



335 **3.3 Drought risk for agricultural systems (irrigated and rain-fed combined)**

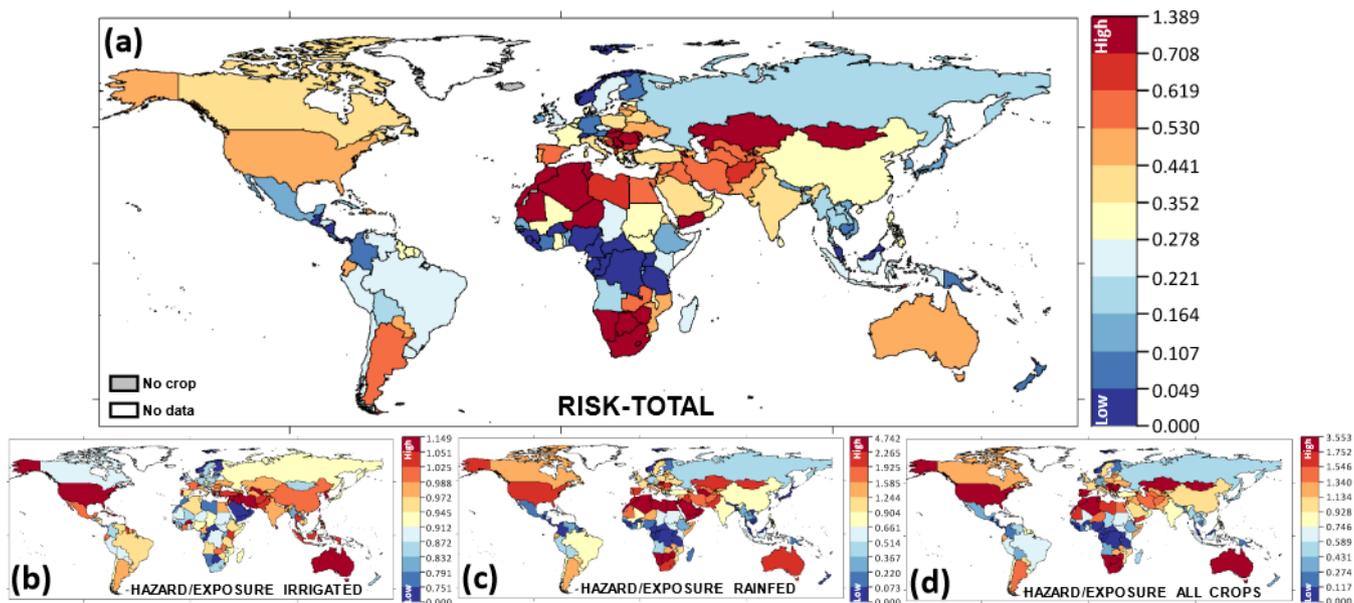


Fig 04. Drought risk (a), hazard/exposure of irrigated (b), rain-fed (c), and the whole crop production sector (d). The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest 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 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



355 renewable water (Supplementary (S3)). Table 02 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 02. 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	
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

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Seven out of the ten countries with the highest overall drought risk are located on the African continent. However, Armenia, Yemen and Hungary also possess high risk levels (Table 02). Botswana ranks as the country with the highest drought risk mainly due to its high exposure combined with its relatively high vulnerability (S1).

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In general, the countries that present higher drought risk have a high amount of exposed crops. Vulnerability varies among them, with Yemen being the country with the highest vulnerability. The lack of coping capacity and social-ecological susceptibility were determinant factors for countries like 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 that have in contrast limited coping capacities,

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is notably higher (S1). The analysis also reveals that, although risk is currently zero in several countries (e.g. DRC, C.A.R., Uganda, etc.), this could rapidly change once these countries are affected by droughts given their very high vulnerability.

375 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
380 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. 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 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.
385 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).

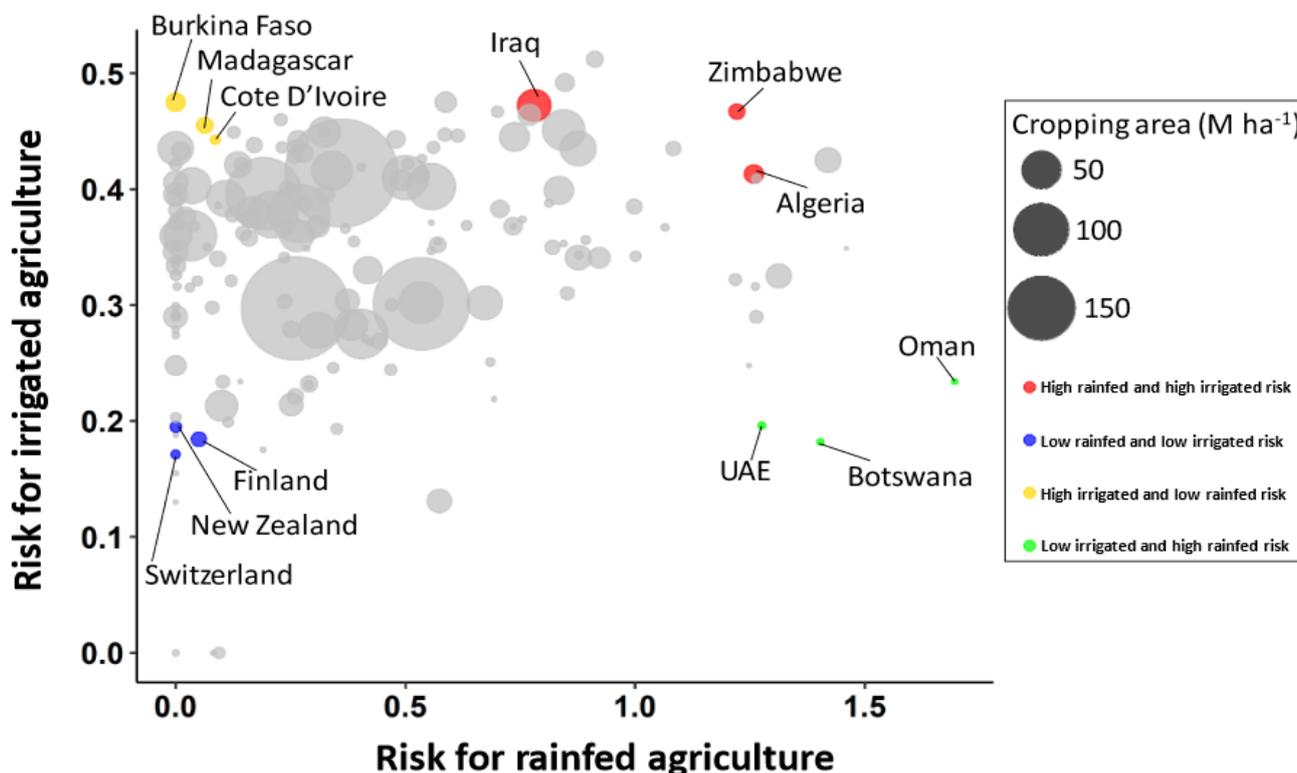


Fig. 05 Country profiles contrasting the drought risk of irrigated and rain-fed agricultural systems. The size of the bubbles indicates the crop growing area (sum of rain-fed and irrigated areas based on MIRCA units).

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3.4 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, 06c). There is also good agreement for countries in southern Africa and northwest Africa with very high drought risk and many registered drought events and for countries with intermediate drought risk such as Canada, Australia or Spain. However, some disagreement between calculated risk and the number of reported drought events is acknowledged. For instance, in 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,

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northwest India and southern Russia are complemented with other regions of low drought risk (Fig. 06b). Therefore, the high number of registered drought events in EM-DAT is corroborated by the presence of high regional drought risk.

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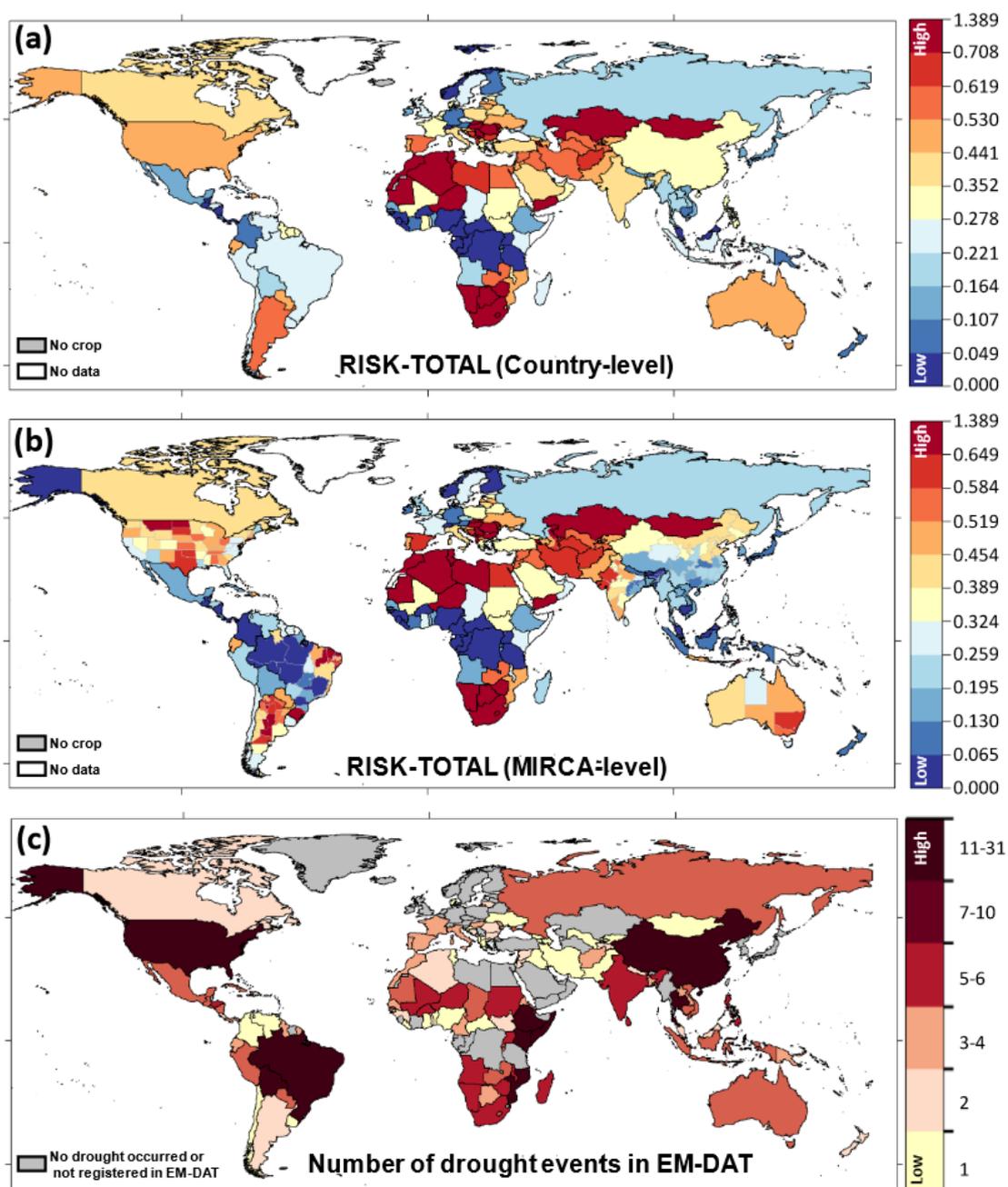


Fig 06. Validation of total risk against drought impact data



4 Discussion

410 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 irrigations water requirement
415 (*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,
southeastern Europe, the Arabian Peninsula and Mongolia for rain-fed systems, Italy, Turkey and Western Mexico for irrigated
420 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 rainfed 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
425 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 rainfed crops in relative terms (*CH_RfAg*).

430 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
435 should be used to rank or compare countries within the rain-fed or irrigated domain but not in between. 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
440 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 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 studies.

The multi-dimensional nature of vulnerability of agricultural systems is represented by a set of 26 expert-weighted indicators, comprising 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).

Nevertheless, the findings of the drought risk assessment correspond to the findings of Carrão et al. (2016), who also found southern and northern Africa as well as the Middle East to be severely at risk. Moreover, 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 focused 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.

However, despite 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 the global scale, the exposure analysis is based on MIRCA data from the year 2000 (Portmann et al., 2000). 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



475 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 01). 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 weigh drought
vulnerability indicators according to their relevance brings subjectivity to the assessment, which necessitates a strong network
480 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
485 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.
This gap has also been highlighted in a recent review of climate vulnerability assessments (Sherbinin et al., 2019) in general,
490 as well as in a recent review of drought risk assessments (Hagenlocher et al., 2019) in particular.

The 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
495 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
500 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.

Lastly, while this presents the first attempt to assess drought risk for agricultural systems, more work is needed to analyze
505 drought risk for other sectors, such as public water supply, tourism, energy production, 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 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.

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